UNIVERSITY OF CAMBRIDGE
Faculty of Economics

Institute for New Economic Thinking

Cambridge Working Papers in Economics

Cambridge-INET Working Paper Series No: 2020/23

Cambridge Working Papers in Economics: 2040

WORK TASKS THAT CAN BE DONE FROM HOME: EVIDENCE ON THE VARIATION WITHIN AND ACROSS OCCUPATIONS AND INDUSTRIES

Abi Adams-Prassl
(University of Oxford)

Teodora Boneva
(University of Zurich)

Marta Golin
(University of Oxford)

Christopher Rauh
(University of Cambridge)

(Revised June 2020)

Using large, geographically representative surveys from the US and UK, we document variation in the percentage of tasks workers can do from home. We highlight three dimensions of heterogeneity that have previously been neglected. First, the share of tasks that can be done from home varies considerably both across as well as within occupations and industries. The distribution of the share of tasks that can be done from home within occupations, industries, and occupation-industry pairs is systematic and remarkably consistent across countries and survey waves. Second, as the pandemic has progressed, the share of workers who can do all tasks from home has increased most in those occupations in which the pre-existing share was already high. Third, even within occupations and industries, we find that women can do fewer tasks from home. Using machine-learning methods, we extend our working-from-home measure to all disaggregated occupation-industry pairs. The measure we present in this paper is a critical input for models considering the possibility to work from home, including models used to assess the impact of the pandemic or design policies targeted at reopening the economy.

JEL: J21, J24
Keywords: Working from home, occupations, industry, Coronavirus

Work that can be done from home: Evidence on variation within and across occupations and industries

Abi Adams-Prassl, Teodora Boneva, Marta Golin, and Christopher Rauh*

June 12, 2020

Abstract

Using large, geographically representative surveys from the US and UK, we document variation in the percentage of tasks workers can do from home. We highlight three dimensions of heterogeneity that have previously been neglected. First, the share of tasks that can be done from home varies considerably both across as well as *within* occupations and industries. The distribution of the share of tasks that can be done from home within occupations, industries, and occupation-industry pairs is systematic and remarkably consistent across countries and survey waves. Second, as the pandemic has progressed, the share of workers who can do all tasks from home has increased most in those occupations in which the pre-existing share was already high. Third, even within occupations and industries, we find that women can do fewer tasks from home. Using machine-learning methods, we extend our working-from-home measure to all disaggregated occupation-industry pairs. The measure we present in this paper is a critical input for models considering the possibility to work from home, including models used to assess the impact of the pandemic or design policies targeted at reopening the economy.

JEL: J21, J24

Keywords: Working from home, occupations, industry, Coronavirus, Covid-19, telework

*Adams-Prassl: University of Oxford (email: abi.adams@economics.ox.ac.uk). Boneva: University of Zurich (email: teodora.boneva@econ.uzh.ch). Golin: University of Oxford (email: marta.golin@nuffield.ox.ac.uk). Rauh: University of Cambridge, Trinity College Cambridge (email: cr542@cam.ac.uk). Ethics approval was obtained from the Central University Research Ethics Committee (CUREC) of the University of Oxford: ECONCIA20-21-09. We are grateful to the Economic and Social Research Council, the University of Oxford, the University of Zurich, the Cambridge INET, and the Cambridge Keynes Fund for generous financial support, and Marlis Schneider for excellent research assistance. The survey and predicted measures of tasks that can be done from home are available for download at `www.covidinequalityproject.com`.

1 Introduction

The onset of the Covid-19 pandemic has exposed differences across workers which received little attention in the past. Most notably, differences in workers' ability to work from home have become extremely salient. With lockdown and social distancing measures in place, telework has often been the only way for non-essential workers to carry out their work (Adams-Prassl et al. 2020*a*; Bick and Blandin 2020).

To understand the labor market impacts of the pandemic and to design better targeted policies, it is crucial to gain a better understanding of the extent to which workers differ in their ability to shift their activities to the home office. Given that economic hardship will be related to the extent to which workers can perform their jobs from home, it is necessary to know whether workers' ability to work from home varies systematically across *and* within occupations and industries, and whether it differs across workers with different background characteristics such as gender or education. Understanding how the ability to work from home is distributed across the population can inform policies aimed at re-opening the economy but also family policies aimed at promoting the ability of working parents to reconcile work and family life in non-pandemic times.

A chief obstacle to studying heterogeneity in the ability to work from home is a lack of appropriate data. To study individual differences in the ability to work from home, it is necessary to obtain reliable individual-level information on the extent to which different workers can do their jobs from home. The measure used to capture individual differences in the ability to work from home needs to have the following four qualities: (i) it needs to be quantifiable and inter-personally comparable, (ii) it needs to be measured on a continuous scale, (iii) it needs to be measured at the individual level, and (iv) it needs to be administered to large representative samples which include workers with different background characteristics in a broad range of different jobs.

To the best of our knowledge, no recent datasets are available that contain such rich information on workers' ability to work from home. Previous studies have drawn on occupation-level data from the Occupational Information Network (O*NET) to assess the feasibility of working from home for each occupation.[1] While this recent work has produced many important insights, indices which are constant across workers within

[1] See, e.g., Baker (2020); Boeri, Caiumi and Paccagnella (2020); del Rio-Chanona et al. (2020); Dingel and Neiman (2020); Gottlieb, Grobovšek and Poschke (2020); Lekfuangfu et al. (2020); Mongey, Pilossoph and Weinberg (2020).

occupations mask a considerable degree of heterogeneity stemming from firm and worker differences. Therefore, the existing measures do not allow us to obtain a full picture of the distribution of the ability to work from home across different workers in the population.

We fill this gap in the literature by developing a new quantifiable, inter-personally comparable survey tool, which we administer to large geographically representative samples in several different countries. For the purpose of this study, we use the three waves of data collected in March, April, and May 2020 as part of the COVID Inequality Project in the United States and the United Kingdom (N=24,924). To capture individual ability to work from home, we ask survey respondents to state what share of job tasks they could do from home. Responses are recorded on a continuous 0-100% scale thus allowing us to capture individual differences in the realities workers face. We combine this individual-level information on the ability to work from home with information on workers' job characteristics (e.g. occupation, industry) as well as information on workers' background characteristics (e.g. gender, age, education). We use these rich data to make several contributions to the literature. We first document the variation in the share of tasks that can be done from home both across as well as within occupations and industries. Our analysis reveals striking systematic patterns that are remarkably consistent across countries and within countries across survey waves. Our data further allow us to detect changes in the ability to work from home over the pandemic and to examine which individual characteristics predict the share of tasks that can be done from home.

Several results emerge from our study. First, we document that there is a high degree of heterogeneity in workers' ability to work from home. While on average respondents in the US and UK report being able to do 42% and 39% of their work tasks from home respectively, a non-negligible share of workers reports values of 0 or 100%. At the same time, the vast majority of workers report values that lie strictly between 0 and 100% highlighting the importance of using a continuous metric.

Second, we document large differences in workers' ability to work from home not just across but also *within* occupations and industries. We find that occupation and industry fixed effects can only account for about one quarter of the variation in the share of tasks workers report being able to do from home. Alternative measures that assume that the ability to work from home is constant within occupations or industries mask a considerable degree of heterogeneity across workers; they cannot capture the complex work realities people face. In Adams-Prassl et al. (2020*a*) we show that the ability to work from home significantly predicts job loss due to the pandemic *over and above* what can be predicted by occupation and industry fixed effects. To fully understand the economic consequences of the pandemic and how policies can help buffer the economic shocks, it is crucial to take differences across workers within occupations and industries into account.

One potential concern is that the limited explanatory power of the occupation and industry fixed effects could be explained by measurement error in our working-from-home measure. While we cannot rule out that some measurement error exists, we provide evidence from six independent surveys done in two countries at three different points in time to show that the variation in our metric is instead systematic. For instance, we examine the mean, median, standard deviation, coefficient of variation and share of respondents reporting 0 or 100% across occupations, industries or occupation-industry pairs and find very high correlations in these statistics across the different countries and independent survey waves.

We further examine the distributions of our working-from-home measure within occupations and industries in more detail. Some striking patterns emerge. For some occupations, for instance 'Architecture and Engineering', many respondents report being able to do an intermediate share of tasks from home and the distribution can be well approximated by a normal distribution. However, for other occupations, for instance 'Office and Administrative Support', the distribution is bi-polar with many workers within that occupation being able to do either very few or almost all tasks from home. These patterns provide important insights for the design of labor market policies aimed at buffering the economic shock of the pandemic. Furloughing schemes, for example, typically allow workers to either keep working at 100% or to stop working altogether. Such policies may not provide enough flexibility for workers in occupations or industries in which most workers can do an intermediate share of their job tasks from home. Short-time work schemes, on the other hand, might be more suitable as they allow employers to reduce workers' hours more flexibly. Another important finding which emerges is that there are no occupations or industries in which the average (mean) worker can do all or none of their tasks from home. This stands in contrast with existing measures, according to which up to almost half of all occupations are characterized by zero possibility of working from home. Policies targeting specific occupations or industries need to take the heterogeneity within those groups into account.

We also consider the time trends in ability to work from home in more detail. We find that the share of tasks that can be done from home increased between March and

May. It appears that this increase is mainly driven by an increase in occupations in which many workers were already capable of doing all tasks from home. Whether this increase is driven by new investments in technologies that facilitate working from home is an open question future research should address.

Finally, we document large differences in the ability to work from home across workers with different characteristics. Male workers, as well as workers with a university degree, report that they can do a significantly higher share of their job tasks from home. Remarkably, these gaps persist even once we control for occupation and industry fixed effects. In Adams-Prassl et al. (2020*a*) we show that women were significantly more likely to lose their jobs compared to men over the pandemic, and that people with a university degree were significantly less likely to lose their jobs. We further show that occupation and industry fixed effects as well as workers' ability to work from home explain all the education gap in job loss, and about half the gender gap. Understanding differences in the ability to work from home across workers helps us understand why different groups were differentially affected by the onset of the pandemic.

The results from our study have clear implications for the design of labor market policies targeted at buffering the impacts of the Covid-19 pandemic. They can also help us identify which bottlenecks exist to home office work and what investments need to be made to facilitate working from home. The Commission on Creating a Global Health Risk Framework for the Future, consisting of an independent group of experts, warned in 2016 that the rate of emergence of infectious diseases is increasing and that there is a 20% chance of the world being hit by four or more pandemics during the next 100 years (Gulland 2016). What may be considered a luxury in normal times may become a necessity as the world of work is confronted with such new challenges.

Arguably, our results also have broader implications for non-pandemic times as we highlight important differences that have received little attention in the past. Gender differences in the ability to work from home, for example, may explain some of the gender gap in labor force participation rates, as the ability to work from home may facilitate the ability to reconcile work and family life. Studying whether the ability to work from home plays a role in parents' decisions to work as well as understanding what may be driving gender differences in the ability to work from home, which we even observe within occupations and industries, are important avenues for future research.

The data generated as part of this project can be used as inputs for macroeconomic models that incorporate the possibility of working from home. Such models can for example be used to assess the impact of the pandemic or to design policies targeted at reopening the economy. We provide a toolkit for each occupation and industry which contains information on the mean, median, standard deviation, and the shares of respondents who can do all or zero tasks from home. Moreover, when the sample size permits, we also provide these highly consistent measures for occupation-industry pairs. Our measures can be used in models based on a sectoral approach (e.g. Baqaee and Farhi 2020; Brinca, Duarte and Faria-e Castro 2020; Bodenstein, Corsetti and Guerrieri 2020) or in an approach based on industries combined with occupations (e.g. Alon et al. 2020; del Rio-Chanona et al. 2020; Kaplan, Moll and Violante 2020; Papanikolaou and Schmidt 2020). We also use a machine-learning algorithm, i.e. a random forest, to train a model that predicts the share of tasks that can be done from home using tasks specified by the O*NET data. This allows us to expand our dataset to include almost 1,000 disaggregated occupations and almost 80,000 occupation-industry pairs.[2]

We build on and contribute to several strands of the literature. First, we contribute to the literature which has assessed the feasibility of working from home for workers in different occupations using occupation-level data (see, e.g., Baker 2020; Boeri, Caiumi and Paccagnella 2020; del Rio-Chanona et al. 2020; Dingel and Neiman 2020; Gottlieb, Grobovšek and Poschke 2020; Lekfuangfu et al. 2020; Mongey, Pilossoph and Weinberg 2020). The occupation-level indices used in these studies are primarily constructed based on O*NET data and manual classification. We contribute to this work by measuring the ability to work from home at the individual level and investigating how the ability to work from home varies across and within occupations and industries, as well as across workers with different characteristics. Second, our paper relates to the literature documenting the prevalence of alternative work arrangements including telework before and during the pandemic as well as individual preferences for alternative work arrangements (e.g. Oettinger 2011; Mas and Pallais 2017, 2020; Hensvik, Le Barbanchon and Rathelot 2020; Beck, Blandin and Mertens 2020; Brynjolfsson et al. 2020; Barrot, Grassi and Sauvagnat 2020). We contribute to this strand of the literature by documenting what fraction of tasks workers report they *could* do from home, i.e. what would be technologically feasible. Whether workers who could work from home do so will depend on a range of different factors such as worker preferences and the cost to firms of offering different work arrangements. The pandemic forced many workers to stay at home and it remains to be seen whether a more general shift to the home office will be observed once the pandemic ends. Finally, our paper also relates to previous

[2] All survey and predicted measures of tasks that can be done from home are available for download at `www.covidinequalityproject.com`.

work studying the impact of working from home on productivity (e.g. Bloom et al. 2015; Angelici and Profeta 2020).

2 Data

To provide evidence on the share of tasks that can be done from home across workers in different occupations and industries, we exploit three independent waves of survey data that we collected between late March and late May in the US and the UK.[3] The sample consists of survey respondents who are resident in the US or the UK, aged 18 years or older, and who must have been engaged in paid work at any point during the 12 months prior to data collection. In each country, no individual was surveyed twice, and in each wave, we sampled around $4,000$ individuals, for a total sample size of $24,924$ respondents. We use quota-based sampling to ensure geographical representativeness in terms of area codes in the US and regions in the UK.[4] Appendix Table A.3 reports information on the background characteristics of respondents in our samples, separately for each survey wave, and compares it to the characteristics of representative samples of the working population in the US and the UK. The latter is taken from the February 2020 monthly CPS data for the US and the 2019 Labour Force Survey data for the UK. Compared to the nationally representative data, our geographically representative samples for both the US and the UK include somewhat younger individuals, a larger share of women, and more workers with a college degree.

To capture heterogeneity in the share of tasks that can be done from home, we ask respondents in all survey waves to report what share of tasks they could do from home in their main job or in their last job, if they report being out of work.[5] We record answers to this question on a continuous scale ranging from 0 to 100%. We illustrate the question with the help of examples, e.g. *'Andy is a waiter and cannot do any of his work from home (0%)'* or *'Beth is a website designer and can do all her work from home (100%)'.* This question allows us to capture heterogeneity in the proportion of

[3]All survey data were collected by the professional survey company Pureprofile; the three different waves were collected on March 24-26, 2020, April 9-14, 2020, and May 20-21, 2020, respectively.

[4]For a comparison of the distribution of our respondents across the relevant geographic areas to the national distribution of the population aged 18 or above in the two countries of interest, see Appendix Tables A.1 and A.2.

[5]In particular, individuals who report having a job are asked *'In your main job, what percentage of the tasks could you do from home?'*, while individuals who report being out of work are asked *'In your last job, what percentage of the tasks could you do from home?'*. A similar question has previously been included in the Understanding America Study (Mas and Pallais 2020).

tasks workers could do from home across respondents. Aggregating individual responses allows us to construct detailed measures on the shares of tasks that can be done from home for different occupations or industries.

In all countries and survey waves, we collect information on the occupation of the respondents' main job if they report having a job or their last job if they report being out of work. Occupations are classified according to the Standard Occupations Classification 2018 major groups (or Job Families). In the early April and late May survey waves, we additionally ask for the industry the respondents work in or used to work in, following the Standard Industry Classification. In the late May survey wave, we also collect information on the detailed occupation and industry classification of the respondent's main or last job. The detailed breakdown for occupations matches the 8-digit SOC codes, and detailed industry classifications are provided at the Division level. The occupation and industry classifications span 23 different occupations and 22 different industries when we use the coarse measures, and 1110 and 86 possible occupations and industries when we use the detailed breakdown.

The data further contain information on the background characteristics of respondents, including age, gender, and educational attainment. We additionally ask respondents to report their gross individual annual earnings from all sources for 2019. Throughout, we restrict the sample to respondents who are either still in work at the time of data collection or report having been in paid work at any time since February.

3 Working from home

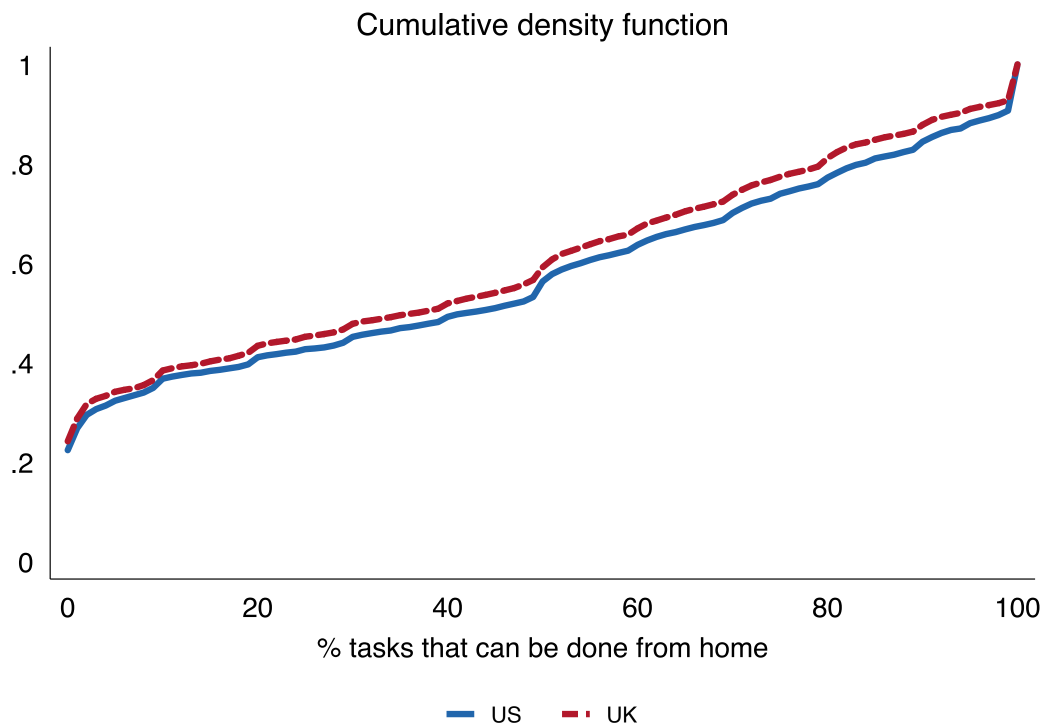
3.1 Mean and median shares

Using our novel survey data, we first document that there is considerable variation in the percentage of tasks workers can do from home. Across all survey waves, respondents in the US (UK) on average report being able to do 43% (41%) of their tasks from home. Figure 1 displays the cumulative distribution function for the share of tasks individuals can do from home in the US (blue solid line) and the UK (red dashed line). The distributions for the US and UK track each other very closely and display the high degree of heterogeneity in the working-from-home measure.[6] While a non-negligible

[6] In Appendix Figure B.1 we further break down the cumulative distribution functions by survey wave and see that they track each other closely as well. For an analysis of changes over time see Section 3.6.

share of workers in both countries reports values of zero or 100%, the vast majority of workers reports shares that lie strictly between zero and 100%, highlighting the fact that the ability to work from home is best captured by a continuous metric.

Figure 1: Distribution of Tasks that can be done from home



Notes: The figure shows the cumulative density function (CDF) of the share of tasks that individuals report being able to do from home in their main or last job. The blue solid line and red dashed line represent the CDF for the US and the UK, respectively.

Consistent with the results from previous studies, we find significant differences across occupations, and we also document significant differences across industries. The mean share of tasks that can be done from home varies significantly across occupations, ranging from 14% for 'Food Preparation and Serving' to 68% for 'Computer and Mathematical' (see column 1 of Table 1). Similarly, there are large differences in mean shares across industries (see column 1 of Table 2). The mean ranges from 18% for 'Accommodation and Food Service Activities' to 70% for 'Information and Communication'.[7]

While differences in mean shares across occupations and industries are sizeable,

[7]In Appendix Tables B.1 and B.2 we present the measures separately by country.

we also find a considerable degree of heterogeneity *within* occupation and industry. Within each occupation and industry, the standard deviation of the working-from-home measure is large (see column 2). Thus, alternative measures that are constant within occupation or industry mask a considerable degree of heterogeneity across workers. This is further reflected in the fact that for many occupations and industries the *median* share of tasks that can be done from home is very different from the *mean* share (see column 3). For example, in 'Food Preparation and Serving' where the mean share is estimated to be 14% the median is 0%. Neglecting heterogeneity within occupation or industry would not give a full account of the realities workers face in the workplace. We explore the dispersion in our working-from-home measure within occupations and industries in more detail in Section 3.2, revealing some striking systematic patterns.

Table 1: Measures of ability to work from home by occupation

Occupation	Mean	SD	Median	Ones	Zeros
Management	56.07	32.63	61	.09	.07
Business and Financial Operations	63.35	29.8	68	.14	.05
Computer and Mathematical	67.61	27.6	72	.16	.02
Architecture and Engineering	54.5	27.73	56	.06	.04
Life, Physical, and Social Science	43.65	32.59	46	.06	.13
Community and Social Service	45.25	35.22	50	.07	.19
Legal	54.15	31.08	53	.06	.07
Educational Instruction and Library	35.06	32.78	27	.06	.16
Arts, Design, Entertainment, Sports, and Media	49.14	36.93	51	.13	.16
Healthcare Practitioners and Technical occ.	25.18	32.38	6	.04	.36
Healthcare Support	29.14	35.88	4.5	.07	.33
Protective Service	22.73	31.11	2	.03	.44
Food Preparation and Serving	13.71	25.83	0	.02	.53
Building and Grounds Cleaning and Maintenance	23.92	32.82	1	.04	.42
Personal Care and Service	21.13	32.72	1	.05	.47
Sales and Related Occupations	26.57	35	2	.05	.4
Office and Administrative Support	53.68	38.4	60	.16	.16
Farming, Fishing, and Forestry	25.22	33.68	6	.07	.27
Construction and Extraction	30.85	33.92	15	.03	.29
Installation, Maintenance, and Repair	29.4	33.59	10	.03	.3
Production	24.74	33.48	2	.04	.42
Transportation and Material Moving	21.39	31.82	1	.03	.45
Military Specific Occupations	36.16	30.06	34	.04	.15

Notes: Mean, standard deviation, and median are computed using a scale from 0-100, i.e. percentages. 'Ones' are the share of respondents reporting 100%, while 'Zeros' are the share of respondents reporting 0%.

Before turning to the dispersion within occupations and industries in more detail, we note that one potential concern with our working-from-home measure is measurement

Table 2: Measures of ability to work from home by industry

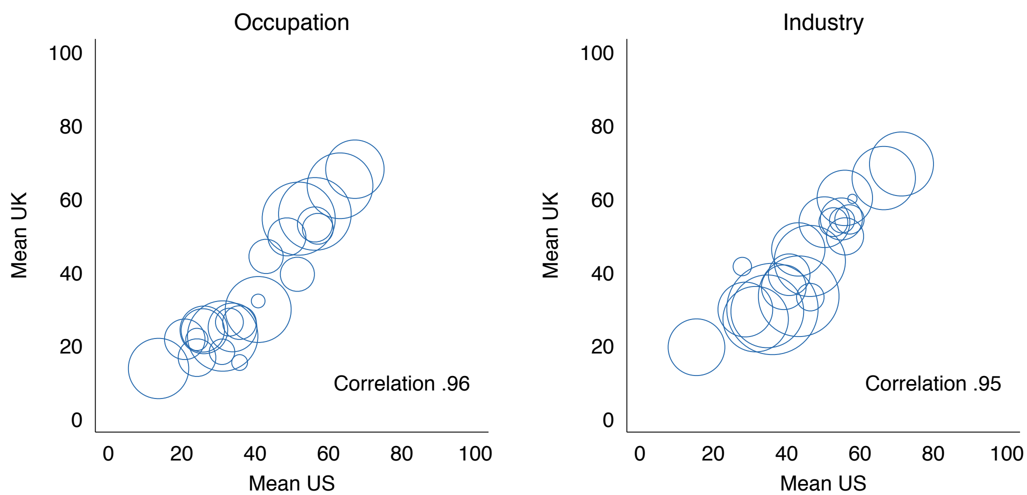
Industry	Mean	SD	Median	Ones	Zeros
Agriculture Forestry and Fishing	41.19	34.75	42	.06	.18
Mining and Quarrying	54.59	23.27	56	.03	.02
Manufacturing	44.44	34.68	49	.06	.19
Electricity, Gas, Steam etc.	52.34	29.59	52	.09	.1
Water Supply etc.	55.39	25.77	57	.04	.04
Construction	44.75	34.14	49	.06	.17
Wholesale and Retail Trade	28.84	34.52	8	.04	.37
Transportation and Storage	37.04	37.71	21.5	.07	.3
Accommodation and Food Service Activities	17.68	28.42	1	.02	.49
Information and Communication	70.37	27.2	77	.17	.02
Finacial and Insurance Activities	66.01	32.31	74	.2	.06
Real Estate Activities	53.16	33.48	53	.09	.1
Professional Activities	57.79	34.67	64	.13	.1
Administrative and Support Services	52.28	36.67	55	.16	.12
Public Administration and Defence	54.59	37.68	62	.12	.18
Education	37.71	34.82	30	.07	.18
Human Health and Social Work	31.62	35.59	10	.06	.29
Arts, Entertainment and Recreation	40.01	38.3	30	.11	.27
Other Service Activities	29.22	36.84	5	.09	.35
Activities of Households as Employers	35.58	35.28	35.5	.05	.27
Extraterritorial Organisations	58.69	27.38	59	.13	.06
Other	33.04	38.29	8	.09	.36

Notes: Mean, standard deviation, and median are computed using a scale from 0-100, i.e. percentages. 'Ones' are the share of respondents reporting 100%, while 'Zeros' are the share of respondents reporting 0%.

error. Given the self-reported nature of the survey measure we use, it may be that people are not paying sufficient attention to the question while answering the survey or that they may interpret the question differently, thus contributing to noise in the measure. While we cannot rule out that some measurement error exists, we provide evidence that the relationships are systematic by comparing the results across independent survey waves and countries.

We first investigate whether the *mean* shares of tasks we estimate for each occupation and industry (column 1 in Tables 1 and 2) are similar in the US and the UK. For this purpose, in Figure 2 we plot the mean tasks that can be done from home within each occupation (left) and industry (right) in the UK (y-axis) against the mean shares we estimate for the US (x-axis). The size of each bubble is proportional to the number of observations for each occupation and industry. As can be seen from these figures, the mean shares we estimate are remarkably similar in the two countries. The estimated mean shares exhibit a correlation of 0.96 (occupations) and 0.95 (industries) across the two countries. We further investigate whether the correlations are similarly high if we investigate the cross-wave, within-country correlations. These relationships are illustrated in Appendix Figures B.2 and B.3, which display a similarly high correlation, which ranges from 0.93 to 0.97. Given that no survey participants were surveyed twice, this lends strong support to the fact that the mean shares we estimate are reliable metrics, revealing systematic patterns.

Figure 2: Mean tasks that can be done from home in the US and the UK by occupation (left) and industry (right)



Notes: Each bubble is proportional to the number of observations and represents one occupation (left) or industry (right). The sample includes both the US and UK data.

An alternative to using the mean is the *median*. We investigate whether the correlation between the median values we estimate for each occupation and industry is similarly high across countries and survey waves. In Figure 3 we show that that there is a strong correlation between the median values in the UK and the US (0.97 for occupations and 0.94 for industries), and that the relationships are similarly strong across survey waves within countries, with values ranging from 0.92 to 0.98 (see Appendix Figures B.4 and B.5).

Having established the high correlation between the mean and median measures across countries and waves, we explore the extent to which these measures correlate with the two different measures provided in Dingel and Neiman (2020), which are based on manual classification and O*NET classifications, respectively. In Appendix Figures B.6 and B.7 we show that our mean and median measures correlate highly with the measures provided by Dingel and Neiman (2020), with correlations ranging between 0.86 and 0.90, lending additional credibility to the measures constructed using different methodologies. There is one notable difference between the mean/median shares we estimate and the measures provided by Dingel and Neiman (2020). As can be seen in the two figures, we have fewer measures close to 0% and 100%, i.e. our spread is smaller.

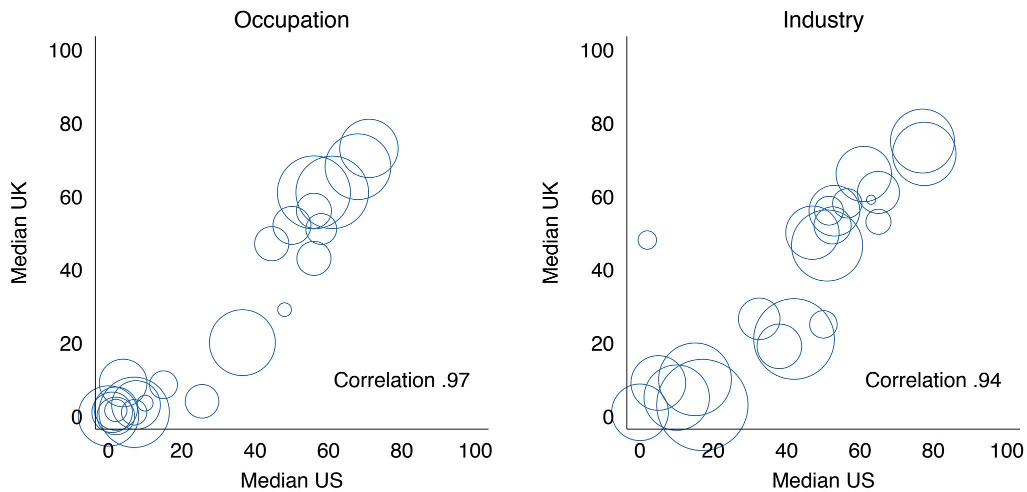
Similar to Mongey, Pilossoph and Weinberg (2020), we find a strong negative correlation between the share of tasks that can be done from home within an occupation and the physical proximity indicator computed using O*NET. In Appendix Figure B.8 we compare our mean and median measures of the share of tasks that can be done from home to the physical proximity indicator and find negative correlations of -0.60 and -0.59, respectively. Given that the share of workers with sick pay tends to be lower amongst workers in occupations that are done at high physical proximity (Adams-Prassl et al. 2020*b*), this relationship could play a particular role in the transmission of airborne viral diseases such as Covid-19.

3.2 Dispersion

So far the literature has assumed that workers within an occupation are equally able to from home. We find considerable heterogeneity in the ability to work from home within occupations and industries, as is illustrated by the high standard deviation of the working-from-home measure within occupation and industry (column 2 of Tables 1 and 2). We find that amongst occupations the standard deviation ranges from 28% for 'Computer and Mathematical' to 38% for 'Office and Administrative Support', while for industries it ranges from 23% for 'Mining and Quarrying' to 38% for 'Arts, Entertainment and Recreation'.

Figure 4 plots the coefficient of variation, i.e. the standard deviation deflated by the mean, for the share of tasks that can be done from home within occupation (left) and industry (right) in the US (x-axis) and UK (y-axis). The coefficients of variation are

Figure 3: Median tasks that can be done from home in the US and the UK by occupation (left) and industry (right)



Notes: Each bubble is proportional to the number of observations and represents one occupation (left) or industry (right).

remarkably similar in the two countries. The correlation between the coefficient of variation within occupations and industries across countries is 0.97 and 0.94, respectively. In Appendix Figure B.9 we perform a similar analysis using the standard deviation and find large positive correlations between the US and UK as well. This strengthens the claim that the variation of shares that can be done from home within occupations and industries is systematic. In Appendix Figures B.10 and B.11 we show that these relationships also hold within countries across survey waves for both the coefficient of variation and the standard deviation, respectively.

Differences in means and standard deviations across occupations and industries highlight the fact that the share of tasks that can be done from home varies considerably across workers both across but also within occupations and industries. We further document that the *shape* of the distribution varies considerably across different occupations and industries, with some distributions being well approximated by bell-shaped curves, while others are left- or right-skewed or bi-modal. Remarkably, we find very similar distributions for the US and the UK.

To illustrate the different patterns, in Figure 5 we plot histograms of the share of tasks that can be done from home for four occupations within the US (blue bars) and the UK (transparent black bars). In the top left panel, we see an example of an occupation, 'Food Preparation and Serving', for which many respondents can do very few tasks from home. The distributions in the US and the UK are virtually identical. The correlation between the shares in the bins between the US and the UK is 0.9989. In the top right panel, we can see that working in 'Computer and Mathematical' occupations, in contrast, allows many respondents to do a large fraction of their tasks from home. However, we also see that a high proportion of workers can do an intermediate share of their tasks from home.

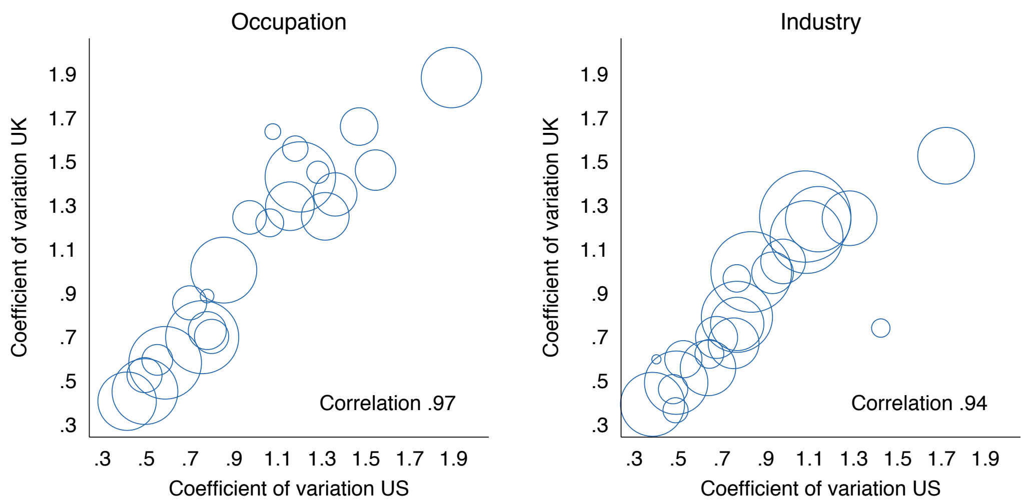
The occupations in the bottom two panels of Figure 5 have very similar mean shares of tasks that can be done from home. For 'Architecture and Engineering' it is 55% and for 'Office and Administrative Support' it is 54% when looking at the entire sample. For those working in 'Architecture and Engineering', displayed on the bottom left, the distribution can be well approximated by a normal distribution. In contrast, the bottom right panel displays a polarized bi-modal distribution for workers in 'Office and Administrative Support', with many workers being able to do close to 0 or 100% of their tasks from home. In Appendix Figures B.12 and B.13 we show the distributions of the remaining occupations and industries. The fact that for each occupation and industry the distributions overlap so closely across countries lends additional credibility to our working-from-home measure.

3.3 All or nothing

Within each occupation, some workers can do all (100%) or none (0%) of their tasks from home. We show that there is considerable variation in those shares across occupations and industries (columns 4 and 5 of Tables 1 and 2), and that those shares are also remarkably similar across countries and independent survey waves.

Amongst occupations, the share of those who can do all tasks from home ranges from 2% for 'Food Preparation and Serving' to 16% for 'Office and Administrative Support' and 'Computer and Mathematical'. Within industries, this share ranges from 5% for 'Activities of Household as Employers' to 17% for 'Information and Communication'. The share of workers who can do zero tasks from home ranges from 2% for 'Computer

Figure 4: Coefficient of variation of tasks that can be done from home in the US and the UK by occupation (left) and industry (right)

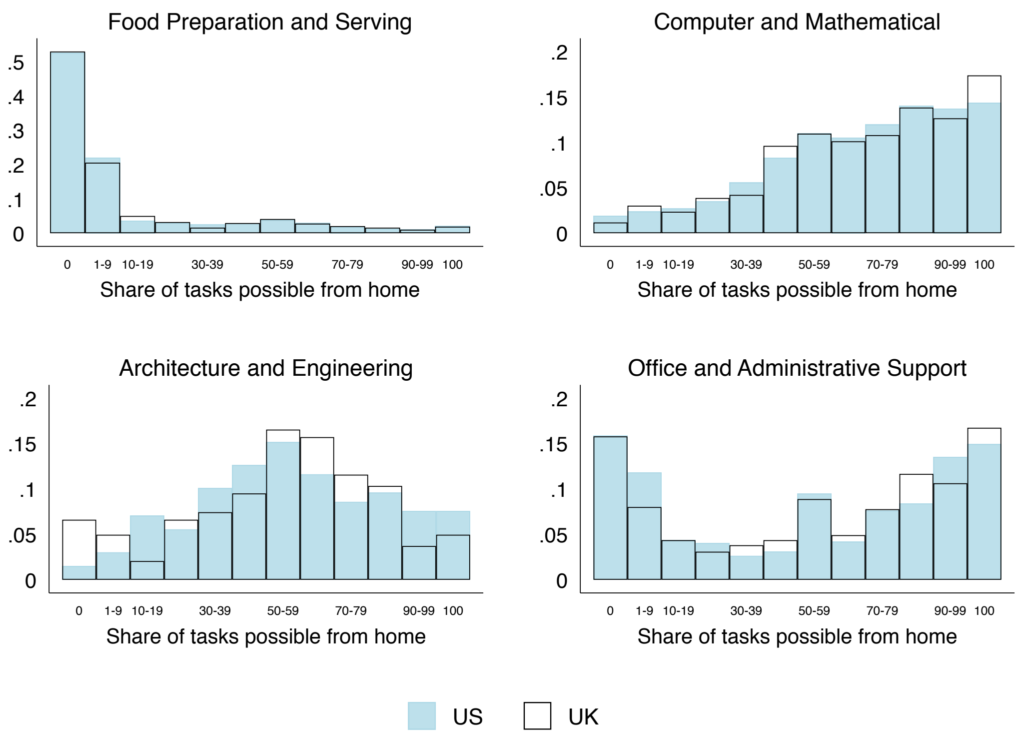


Notes: Each bubble is proportional to the number of observations and represents one occupation (left) or industry (right). The sample includes both the US and UK data.

and Mathematical' to 53% for 'Food Preparation and Serving' amongst occupations, and from 2% for 'Information and Communication' to 49% for 'Accommodation and Food Service Activities' amongst industries.

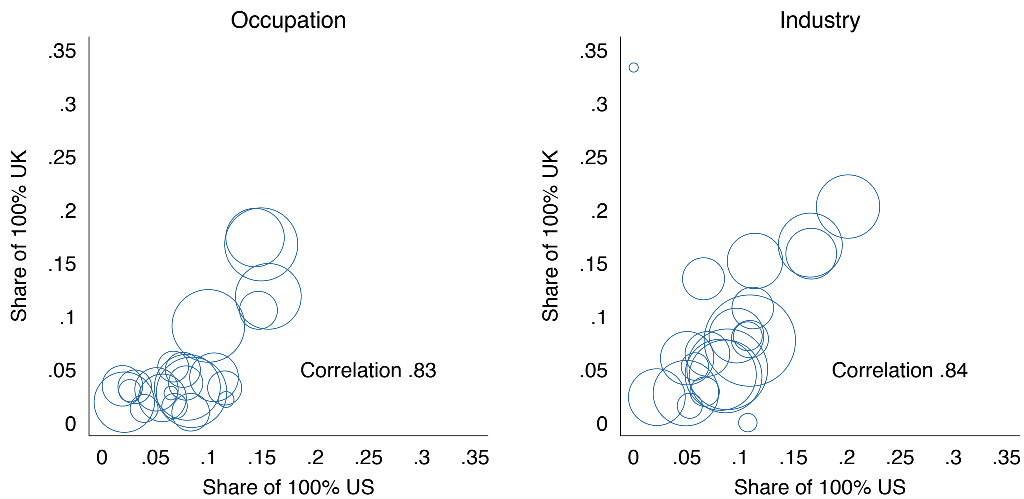
To investigate whether these differences are systematic, we again turn to a comparison across countries and waves. In Figure 6, we see that the correlation between countries for those who can do all tasks from home is 0.83 across occupations and 0.84 across industries. Similarly, for those who can do no tasks from home, we see in Figure 7 that the correlations are 0.97 and 0.93. In Appendix Figures B.14 and B.15 it becomes clear that the corresponding correlations across waves within countries are very high as well.

Figure 5: Distribution of share tasks that can be done from home within occupations



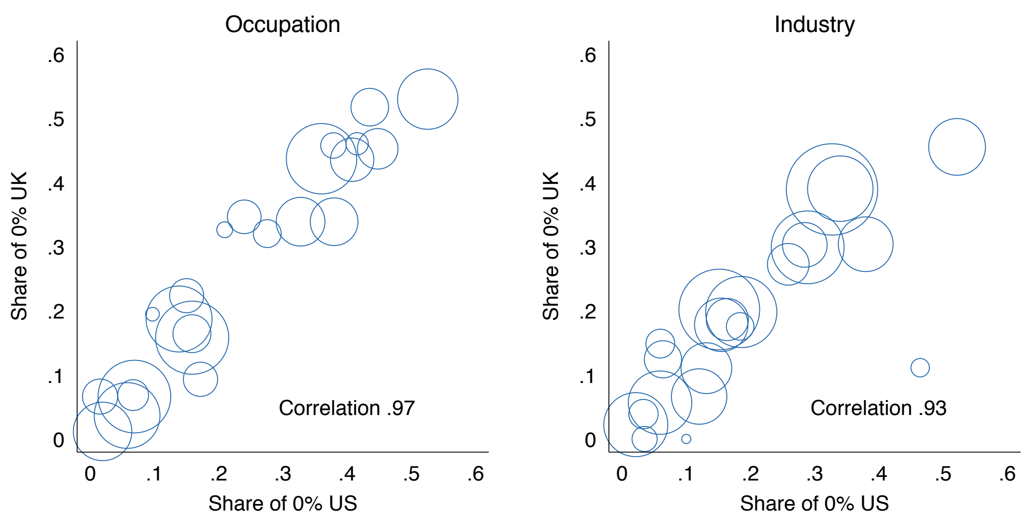
Notes: The light blue bars display the share of responses by bin for the US and the black transparent bars for the UK.

Figure 6: Share of people that can do all tasks from home in the US and the UK by occupation (left) and industry (right)



Notes: Each bubble is proportional to the number of observations and represents one occupation (left) or industry (right). The sample includes both the US and UK data.

Figure 7: Share of people that cannot do any tasks from home in the US and the UK by occupation (left) and industry (right)



Notes: Each bubble is proportional to the number of observations and represents one occupation (left) or industry (right). The sample includes both the US and UK data.

3.4 Occupations and industries at the disaggregated level

The occupation and industry classifications used in the previous analyses span 23 different occupations and 22 industries. The classifications are coarse and subsume different sub-categories. Our third wave of data also contains disaggregated information, spanning 1110 and 86 possible occupations and industries respectively. We explore the distribution of our working-from-home measure within and across disaggregated occupations and industries to demonstrate that (i) there is also considerable variation within and across those sub-categories, and (ii) the patterns across the US and UK are remarkably similar even when we consider the disaggregated occupation and industry classifications.

In Figure 8 we show the distribution of the share of tasks that can be done from home within four disaggregated occupations by country. Again we see that occupations exhibit similar patterns as at the aggregate level and that distributions in the US and UK overlap closely.

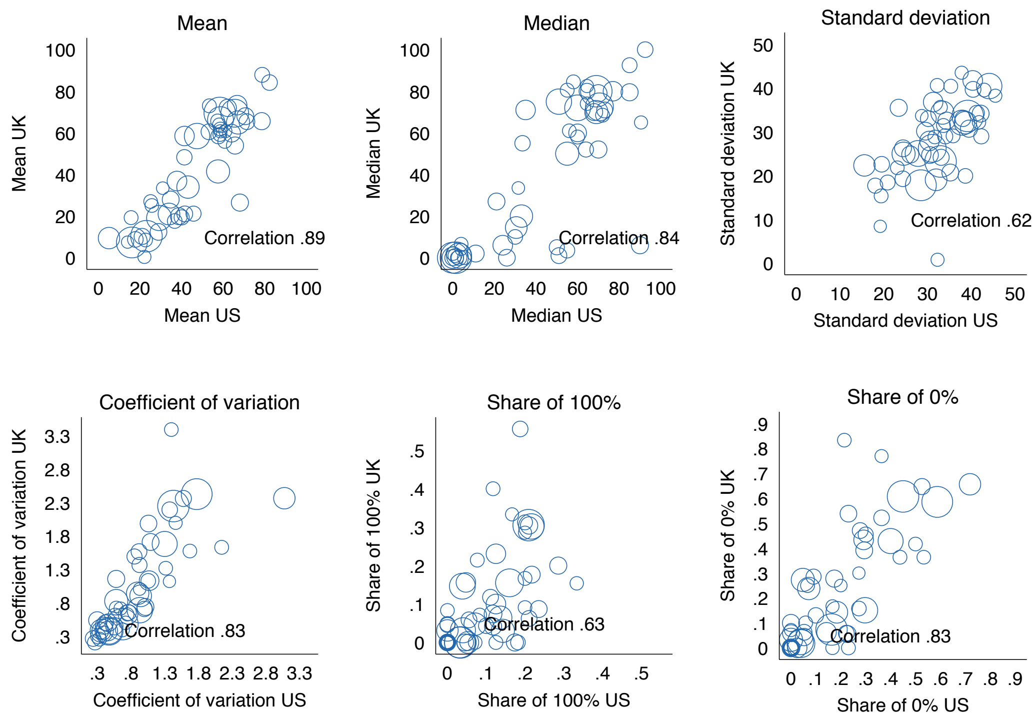
Further, we keep all cells with at least ten observations. Across these fine-grained occupations, the mean share of tasks that can be done from home varies from 3% for 'Bartenders' in the family of 'Food Preparation and Serving Related' occupations to 89% for 'Software Developers, Applications' in the family of 'Computer and Mathematical' occupations. For industries it varies from 16% for 'Food and beverage service activities' in the family of 'Accommodation and food service activities' to 89% in 'Publishing activities' in the family of 'Information and communication' industries.

In Figure 9, we plot the mean, median, standard deviation, coefficient of variation, share of respondents with 100%, and share of respondents with 0% for the disaggregated occupations in the US (x-axis) and the UK (y-axis). The correlations are close to 0.90 for the mean, median, coefficient of variation, and share of respondents with 0%. This suggests that the within variation we document at the aggregated level is unlikely to be solely driven by different occupation types within each family but also by varying shares within a specific sub-occupation. The correlations in Appendix Figure B.16 for industries at the disaggregated level support the same argument for industries.

Figure 8: Distribution of share tasks that can be done from home within disaggregated occupations

Notes: The light blue bars display the share of responses by bin for the US and the black transparent bars for the UK.

Figure 9: Measures of tasks from home in the US and the UK by occupation at two-digit level



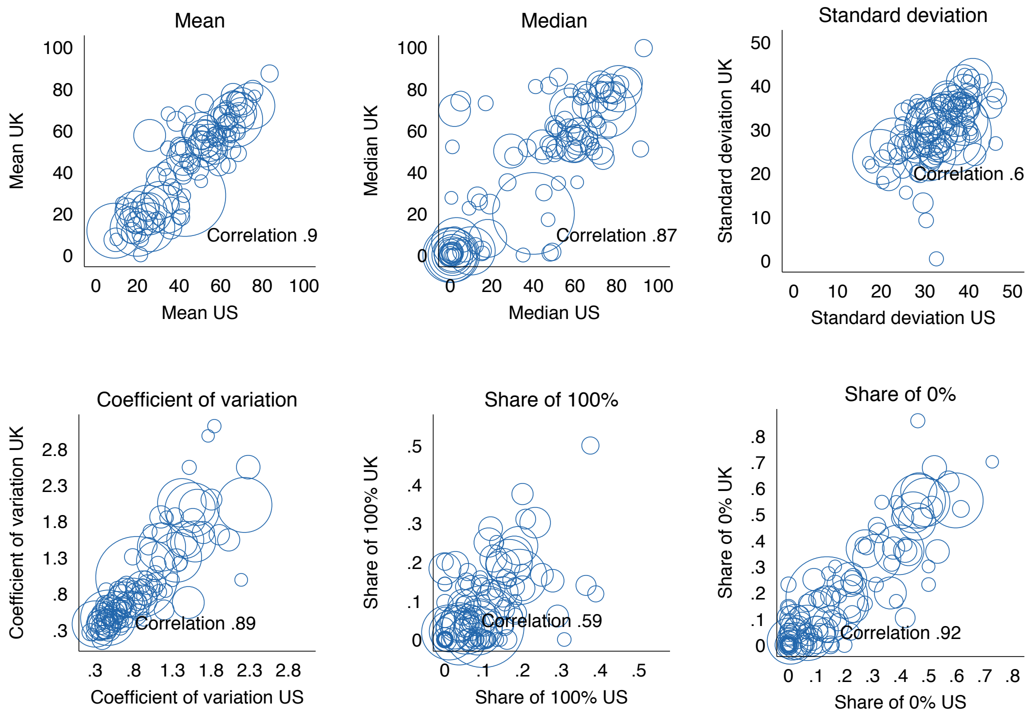
Notes: Each bubble is proportional to the number of observations and represents one occupation at the two-digit level.

3.5 Occupation-industry pairs

We now explore the extent to which the share of tasks that can be done from home varies within occupations across different industries. For that purpose, we examine the mean share of tasks that can be done from home by occupation within industries, i.e. we cross-tabulate occupation and industry. We keep all cells with at least ten observations, which leaves us with 170 occupation-industry pairs. Across the occupation-industry pairs, the share of tasks that can be done from home varies from 5% for the occupation 'Food Preparation and Serving' in the 'Education' industry to 87% for the occupation 'Computer and Mathematical' in the industry 'Financial and Insurance Activities'.

In Figure 10 we plot the mean, median, standard deviation, coefficient of variation, share of respondents with 100%, and share of respondents with 0% for the occupation-industry pairs in the US (x-axis) and the UK (y-axis). We find correlations that are close to 0.90 for the mean, median, coefficient of variation, and share of respondents with 0%. We conclude that our data can not only be used to proxy the share of tasks that can be done from home by occupation and industry, but also by occupation-industry pairs. This even seems to be the case for occupation-industry pairs at the disaggregated level as can be seen in Appendix Figure B.17, though here cell sizes become small.

Figure 10: Measures of tasks from home in the US and the UK by occupation-industry pairs



Notes: Each bubble is proportional to the number of observations and represents one occupation-industry pair. A pair has to have at least 10 observations in each country.

3.6 Changes over time

With the onset of the pandemic, many workers who had not previously worked from home were suddenly expected to do so. Firms had to change processes and the way decisions were made in order to facilitate working from home. Therefore, it is likely that some changes in the share of tasks that can be done from home can be expected.

We regress the share of tasks that can be done from home on time, region, occupation, and industry fixed effects in Table 3. In the first column we can see that the share of tasks that can be done from home increased by 4.1 and 6.2 percentage points in April and May in comparison to March. However, once we control for occupation fixed effects in column 2 these values drop to 2.7 and 4.8 percentage points. Adding industry fixed effects in column 3 reduces our sample to April and May. We find that from April to May the share of tasks that can be done from home increased by 2.2 percentage points, which remains stable to adding occupation fixed effects in column 4 as well. Finally, we split the sample by country and display the results for the US (column 5) and UK (column 6). We find an increase of 3 and 1.4 percentage points from April to May for the US and UK, respectively. In general we find that occupation and industry fixed effects, together with time and region fixed effects, explain about 26% of the variation in the share of tasks that can be done from home.

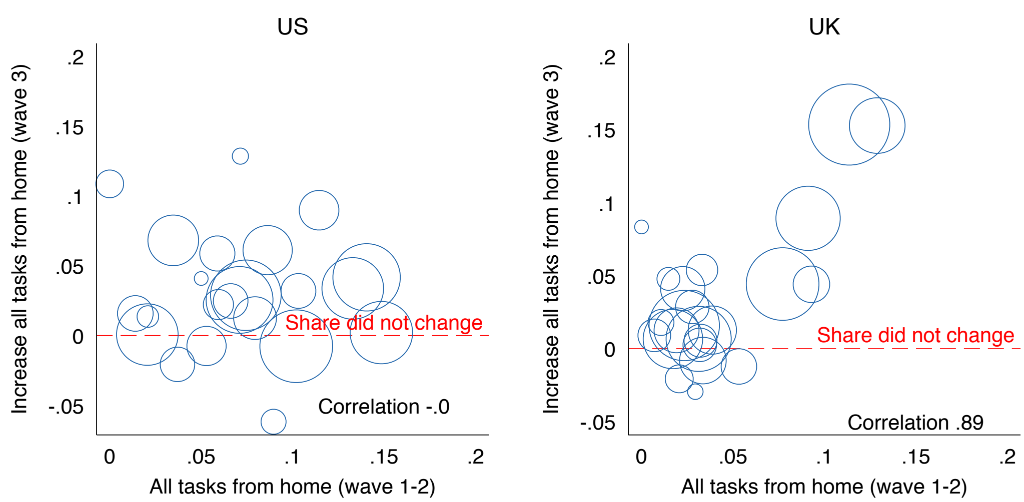
Table 3: Tasks from home over time

	(1)	(2)	(3)	(4)	US (5)	UK (6)
April	0.0410***	0.0268***				
	(0.0066)	(0.0059)				
May	0.0620***	0.0483***	0.0220***	0.0217***	0.0295***	0.0141*
	(0.0067)	(0.0060)	(0.0063)	(0.0059)	(0.0092)	(0.0077)
Constant	0.3199***	0.4791***	0.3667***	0.4749***	0.4713***	0.4777***
	(0.0378)	(0.0345)	(0.0540)	(0.0520)	(0.0598)	(0.0467)
Observations	17971	17971	11865	11865	5332	6533
R^2	0.0247	0.2226	0.1536	0.2598	0.2333	0.2986
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	yes	yes
Industry F.E.	no	no	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Regions are states for the US. The dependent variable is the share of tasks (0-1) respondents report to be able to do from home. In column (5) the sample is restricted to the US and in column (6) to the UK.

Figure B.14 already indicates that within occupations and industries no large shifts in terms of mean or median shares have taken place. However, it appears that there is an increase in the share of respondents who can do all tasks from home. In Figure 11 we look into which occupations saw this increase in the US (left) and the UK (right). On the x-axis we display the average share of respondents reporting to be able to do all tasks from home across the first two survey waves, while on the y-axis we see the increase in the third wave. In the US we see no systematic evidence in the changes. However, for the UK we see that those occupations which already had the largest share of workers who could do all tasks from home also saw the largest increases. In Appendix Figure B.18 we verify that this change has taken place amongst respondents that still have a job. This increase at the top hints towards further job polarization in terms of being able to work from home. Whether this increase has been driven by changes in employees' approaches to their work or whether employers made investments to increase the capacity to work from home cannot be determined with the data at hand.

Figure 11: Increase of share that can do all tasks from home



Notes: Each bubble is proportional to the number of observations and represents one occupation.

3.7 Predicting the working-from-home measure

Using the survey data from the third wave, we have at least 10 observations for 126 out of the 1110 disaggregated occupations. For the remaining occupations, the number of respondents in our sample is below ten, which we consider too few to obtain credible estimates directly from our data. However, we use a machine-learning method to fill this gap and construct the working-from-home measure for all disaggregated occupations. Moreover, we do the same for occupation and industry pairs.

Most approaches quantify the share of tasks that can be done from home for a given occupation by classifying the task list provided by O*NET. We use this task list combined with our individual responses to predict the share of tasks that can be done from home for all disaggregated occupations. To do so, we train a random forest model to predict the mean share of tasks, the likelihood of being able to do zero tasks, and the likelihood of being able to do all tasks from home. As predictors, we include the list of 38 binary work tasks given by the O*NET data. For the first two survey waves, where we only have information on respondents' aggregated occupation, we take the mean share for each work task within that occupation group.

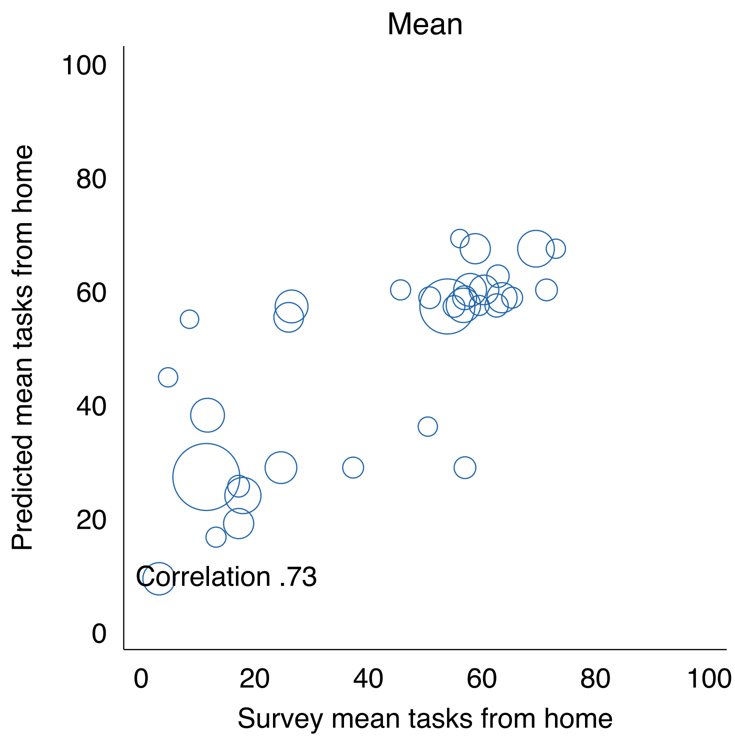
In terms of prediction algorithms, we use a random forest regression tree for the share of tasks due to its continuous nature, while for the binary variables of zero and all tasks we use a random forest classifier. A random forest has the great advantage that it can detect non-linear combinations of work tasks and their relation to the share of tasks that can be done from home. The fact that the predictions are then averaged across many trees, i.e. a random forest, safeguards against overfitting. The tree depths and numbers of trees are determined by three-fold cross-validation.[8]

In Figure 12 we compare the mean share of tasks that can be done from home according to our survey (x-axis) and the predicted mean share by the random forest for the disaggregated occupation codes for which we have at least 10 observations. We find that the correlation between predicted and measured averages is 0.88. However, this could be due to overfitting. In order to test the validity of our prediction model, we train the random forest on 70% of the occupations and then predict out-of-sample on the remaining 30%. The model still provides a reasonable approximation with a correlation of 0.73 between the two measures. This raises the confidence that the extrapolations to other occupations, for which we have no or few observations, provide

[8] The algorithm settles on a depth of 6 and 25 trees for the share of tasks, a depth of 2 and 25 trees for zero tasks, and a depth of 4 and 10 trees for all tasks.

valuable information.

Figure 12: Survey mean versus predicted mean based on O*NET tasks (out-of-sample)



Notes: Each bubble is proportional to the number of observations and represents one occupation.

In Appendix Figure B.19 we show that predicting the share of workers that can do all tasks from home is slightly less successful. Given that we also observe the largest change among this category, it is not surprising that it is less predictable.

We repeat the same procedure, while including the aggregated industry level as a predictor as well. The predictive performance is extremely high as the correlation between survey and predicted means is 0.95. When we again do the out-of-sample verification using 70% of occupation-industry pairs as a training sample and the remaining 30% for out-of-sample prediction, we find a correlation of 0.90 as can be seen in Appendix Figure B.20. We use the trained model to predict the mean share of tasks that can be done from home for each occupation-industry pair. Given that this would be difficult to display at the disaggregated level, in Figure 13 we show a heatmap of the predicted means at the aggregated occupation-industry level. The y-axis displays occupations, while the x-axis classifies industries. The darker the shade of a cell, the more tasks can be done from home. While some occupations, such as ‘Business and Financial Operations’, display high shares across all industries, other occupations, such as ‘Office and Administrative Support’ are characterized by a higher variance. This coincides with our findings from the variations across respondents.

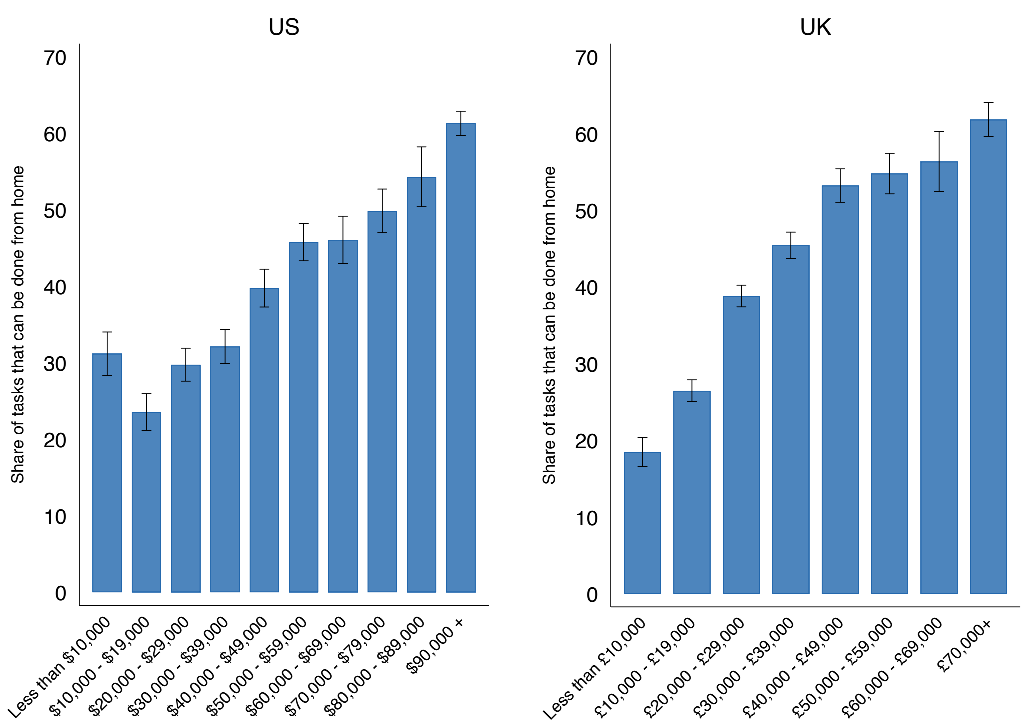
Figure 13: Heatmap of predicted mean for occupation-industry pairs

Notes: The darker the shade of a cell, the more tasks can be done from home. The y-axis displays occupations and the x-axis classifies industries.

4 Who can work from home

Having established differences in the ability to work from home across occupations and industries, we now turn to the question of which individual characteristics predict the share of tasks individuals can do from home. We start by documenting differences across socio-economic background. In Figure 14 we see how the share of tasks that can be done from home is spread across the income distribution. On the x-axis we show total individual gross labor income and on the y-axis the average percentage of tasks that can be done from home. We see that both in the US (left) and the UK (right) those with high incomes can do a substantially larger share of their work tasks from home.

Figure 14: Tasks that can be done from home by gross labor income in 2019



Notes: Earnings are defined as total gross individual labor income in 2019. The black bars represent 95% confidence intervals.

Next we regress the share of tasks that can be done from home on job and individual characteristics. In column 1 of Table 4 we see that time and region fixed effects, which are states in the US and regions in the UK, account for less than 3% of the variation in the share of tasks that can be done from home.

Table 4: Tasks from home

	(1)	(2)	(3)	US (4)	UK (5)
Age	-0.0022***	-0.0021***	-0.0021***	-0.0023***	-0.0018***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Female	-0.0634***	-0.0319***	-0.0215***	-0.0379***	-0.0071
	(0.0053)	(0.0052)	(0.0065)	(0.0102)	(0.0083)
University degree	0.1938***	0.1301***	0.1144***	0.1206***	0.1082***
	(0.0053)	(0.0051)	(0.0064)	(0.0101)	(0.0082)
April	0.0264***	0.0194***			
	(0.0063)	(0.0058)			
May	0.0520***	0.0432***	0.0237***	0.0273***	0.0191**
	(0.0064)	(0.0059)	(0.0058)	(0.0091)	(0.0076)
Constant	0.3735***	0.5107***	0.5123***	0.5267***	0.4800***
	(0.0371)	(0.0347)	(0.0520)	(0.0602)	(0.0484)
Observations	17971	17971	11865	5332	6533
R^2	0.1057	0.2560	0.2853	0.2619	0.3211
Region F.E.	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	yes	yes	yes
Industry F.E.	no	no	yes	yes	yes

Notes: OLS regressions. Standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Regions are states for the US. The dependent variable is the share of tasks (0-1) respondents report to be able to do from home. In column (4) the sample is restricted to the US and in column (5) to the UK.

The share is decreasing in age, 6.3 percentage points lower for women, and 19.4 percentage points higher for university graduates. However, in column (3) we see that once we add occupation and industry fixed effects, the coefficient for the female dummy drops to -2.2 percentage points, and the coefficient for university graduates is nearly halved. Together all these variables explain 29% of the variation in the share of tasks that can be done from home. In columns (4) and (5) we look at the relationships separately for the US and the UK, respectively. While the coefficients for university graduates is similar across countries, the gender difference is driven by the US.

5 Conclusion

In this paper, we exploit new survey data from the US and the UK to document differences in the extent to which workers can perform their tasks from home across occupations and industries. We show that workers' ability to work from home varies considerably both across, and within, occupations and industries. Relatedly, we find large differences across occupations and industries in the share of workers that can perform all or none of their tasks from home. The differences that we find in the share of tasks that can be performed from home are systematic, as they correlate highly both across countries and survey waves. Even within occupation-industry pairs, our measure of ability to work from home strongly correlates across countries.

The mean shares of tasks respondents to our survey report being able to perform from home across occupations and industry correlate highly with existing measures of ability to shift to the home office. However, the evidence presented in this paper highlights the importance of taking variation within industries and occupations into account. We provide the first and second moments, the median, the shares of respondents that can do all or zero tasks from home by occupation and industry (and occupation-industry pairs where sample sizes allow). The importance of being able to work from home as a protector from job loss during the Covid-19 pandemic, above and beyond occupation and industry, has been highlighted by Adams-Prassl et al. (2020*a*). Therefore, we argue that our measures can serve as informative inputs into macroeconomic models accounting for the ability to work from home, a feature that has become particularly important when studying the impact of the Covid-19 pandemic.

Finally, we train a prediction model using the task information from the O*NET to extrapolate to disaggregated occupations for which we don't have information about the share of tasks that can be done from home. We find that the trained model has a high predictive performance. We provide our disaggregated measured and predicted abilities to work from home and emphasize their informativeness for policymakers designing policies that will guide countries through the process of reopening.

For our most recent survey wave in May, we document an increase in the share of tasks that can be done from home at the top end of the distribution. This increase is driven by occupations in the UK that already permitted a large share of tasks to be done from home, suggesting a further expansion of a new form of job polarization. Whether this increase is driven by the adaptation of employers or employees is an exciting question left for future research.

References

Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh. 2020*a*. "Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys." IZA Discussion Papers.

Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh. 2020*b*. "Inequality in the Impact of the Coronavirus Shock: New Survey Evidence for the UK." Cambridge-INET Working Papers.

Alon, Titan, Matthias Doepke, Jane Olmstead-Rumsey, and Michele Tertilt. 2020. "The impact of COVID-19 on gender equality." National Bureau of Economic Research 26947.

Angelici, Marta, and Paola Profeta. 2020. "Smart-working: Work flexibility without constraints." CESifo Working Paper 8165.

Baker, Marissa G. 2020. "Who cannot work from home? Characterizing occupations facing increased risk during the COVID-19 pandemic using 2018 BLS data." *medRxiv*.

Baqaee, David Rezza, and Emmanuel Farhi. 2020. "Nonlinear production networks with an application to the covid-19 crisis."

Barrot, Jean-Noel, Basile Grassi, and Julien Sauvagnat. 2020. "Sectoral effects of social distancing." *Available at SSRN*.

Beck, Alexander, Adam Blandin, and Karel Mertens. 2020. "Work from home after the COVID-19 Outbreak." Working Paper.

Bick, Alexander, and Adam Blandin. 2020. "Real Time Labor Market Estimates-During the 2020 Coronavirus Outbreak." Mimeo.

Bloom, Nicholas, James Liang, John Roberts, and Zhichun Jenny Ying. 2015. "Does working from home work? Evidence from a Chinese experiment." *The Quarterly Journal of Economics*, 130(1): 165–218.

Bodenstein, Martin, Giancarlo Corsetti, and Luca Guerrieri. 2020. "Social distancing and supply disruptions in a pandemic."

Boeri, Tito, Alessandro Caiumi, and Marco Paccagnella. 2020. "Mitigating the work-safety trade-off." Covid Economics.

Brinca, Pedro, Joao B Duarte, and Miguel Faria-e Castro. 2020. "Measuring Sectoral Supply and Demand Shocks during COVID-19." *FRB St. Louis Working Paper*, , (2020-011).

Brynjolfsson, Erik, John Horton, Adam Ozimek, Daniel Rock, Garima Sharma, and Hong Yi Tu Ye. 2020. "COVID-19 and Remote Work: An Early

Look at US Data."

del Rio-Chanona, R Maria, Penny Mealy, Anton Pichler, Francois Lafond, and Doyne Farmer. 2020. "Supply and demand shocks in the COVID-19 pandemic: An industry and occupation perspective." *arXiv preprint arXiv:2004.06759*.

Dingel, Jonathan, and Brent Neiman. 2020. "How many jobs can be done at home?" National Bureau of Economic Research 26948.

Gottlieb, Charles, Jan Grobovšek, and Markus Poschke. 2020. "Working from home across countries." *Covid Economics*, 71.

Gulland, Anne. 2016. "World invests too little and is underprepared for disease outbreaks, report warns." *British Medical Journal*, 352(i225).

Hensvik, Lena, Thomas Le Barbanchon, and Roland Rathelot. 2020. "Which jobs are done from home? Evidence from the American Time Use Survey."

Kaplan, Greg, Benjamin Moll, and Gianluca Violante. 2020. "Pandemics according to HANK." Mimeo.

Lekfuangfu, Warn N, Suphanit Piyapromdee, Ponpoje Porapakkarm, and Nada Wasi. 2020. "On Covid-19: New Implications of Job Task Requirements and Spouse's Occupational Sorting." *Available at SSRN 3583954*.

Mas, Alexandre, and Amanda Pallais. 2017. "Valuing Alternative Work Arrangements." *American Economic Review*, 107(12): 3722–3759.

Mas, Alexandre, and Amanda Pallais. 2020. "Alternative work arrangements." NBER Working Paper 26605.

Mongey, Simon, Laura Pilossoph, and Alex Weinberg. 2020. "Which Workers Bear the Burden of Social Distancing Policies?" *University of Chicago, Becker Friedman Institute for Economics Working Paper*, , (2020-51).

Oettinger, Gerald S. 2011. "The incidence and wage consequences of home-based work in the United States, 1980–2000." *Journal of Human Resources*, 46(2): 237–260.

Office for National Statistics. 2019. "Estimates of the population for the UK, England and Wales, Scotland and Northern Ireland." Data retrieved from `https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesforukenglandandwalesscotlandandnorthernireland`.

Papanikolaou, Dimitris, and Lawrence Schmidt. 2020. "Working Remotely and the Supply-Side Impact of COVID-19." *Available at SSRN 3615334*.

U.S. Census Bureau, Population Division. 2019. "Estimates of the Total Resident Population and Resident Population Age 18 Years and Older for the

United States, States, and Puerto Rico: July 1, 2019 (SCPRC-EST2019-18+POP-RES)." Data retrieved from https://www.census.gov/newsroom/press-kits/2019/national-state-estimates.html.

A Data Description

Table A.1: Distribution of respondents across area codes - US

Region	National	Late March	Early April	Late May
Area code 0	7.40	7.39	7.40	7.41
Area code 1	10.33	10.32	10.33	10.36
Area code 2	10.04	10.04	10.05	10.03
Area code 3	14.41	14.41	14.40	14.45
Area code 4	10.02	10.02	10.03	10.01
Area code 5	5.25	5.25	5.25	5.24
Area code 6	7.17	7.17	7.18	7.16
Area code 7	11.94	11.94	11.95	11.93
Area code 8	7.13	7.12	7.13	7.11
Area code 9	16.30	16.34	16.30	16.30
Observations		4003	4000	4007

Notes: National figures refer to the latest available estimates for the population of residents aged 18 or above and come from the United States Census Bureau. Data source: U.S. Census Bureau, Population Division (2019).

Table A.2: Distribution of respondents across regions - UK

Region	National	Late March	Early April	Late May
Scotland	8.42	8.48	8.54	8.48
Northern Ireland	2.76	2.57	2.80	2.74
Wales	4.79	4.83	4.87	4.79
North East	4.06	4.08	4.12	4.04
North West	11.00	11.02	11.11	10.95
Yorkshire and the Humber	8.24	8.28	8.34	8.21
West Midlands	8.80	8.86	8.92	8.78
East Midlands	7.27	7.32	7.38	7.26
South West	8.59	8.63	8.70	8.61
South East	13.70	13.79	13.87	13.69
East of England	9.29	8.91	8.03	9.30
Greater London	13.15	13.24	13.32	13.15
Observations		3974	4931	4009

Notes: National figures refer to the latest available estimates for the population of residents aged 18 or above and come from the Office for National Statistics. Data source: Office for National Statistics (2019).

Table A.3: Demographic Variables in the Population & Surveys

	US				UK			
	CPS	March	April	May	LFS	March	April	May
Female	0.472	0.621	0.581	0. 616	0.47	0.532	0.552	0.550
University	0.395	0.440	0.494	0.488	0.357	0.422	0.488	0.464
<30	0.231	0.322	0.255	0.340	0.232	0.295	0.281	0.283
30-39	0.224	0.262	0.264	0.243	0.230	0.272	0.333	0.264
40-49	0.203	0.179	0.215	0. 176	0.217	0.203	0.238	0.196
50-59	0.198	0.130	0.136	0. 121	0.217	0.151	0.114	0.163
60+	0.144	0.107	0.130	0.120	0.104	0.079	0.033	0.095

Notes: The table shows the mean demographic characteristics of economically active individuals in each respective country. These were calculated using the frequency weights provides in the CPS for the US and the LFS for the UK. The unweighted averages of these demographic variables in our survey waves are also reported.

B Additional Tables and Figures

Table B.1: Summary statistics for working from home by occupation

	US					UK				
Occupation	Mean	SD	Median	Ones	Zeros	Mean	SD	Median	Ones	Zeros
Management	56.26	32.95	61	.1	.07	55.9	32.38	61	.09	.07
Business and Financial Operations	63.12	31.17	68	.16	.06	63.57	28.47	68	.12	.04
Computer and Mathematical	67.17	27.7	71	.14	.02	68.08	27.5	73	.17	.01
Architecture and Engineering	56.28	27.67	56	.08	.02	53.03	27.74	56	.05	.07
Life, Physical, and Social Science	42.96	34.25	44.5	.08	.17	44.31	31	47	.04	.09
Community and Social Service	51.49	35.9	56	.12	.15	39.44	33.63	43	.03	.22
Legal	57.08	31.39	58	.07	.07	51.84	30.71	51	.05	.07
Educational Instruction and Library	40.82	34.81	36.5	.08	.14	29.84	29.9	20	.03	.19
Arts, Design, Entertainment, Sports, and Media	48.64	37.83	50	.15	.16	49.65	36.05	52	.11	.16
Healthcare Practitioners and Technical occ.	26	34.2	4	.06	.38	24.28	30.29	9	.02	.34
Healthcare Support	33.81	39.02	7.5	.1	.33	24.95	32.27	3	.04	.34
Protective Service	24.09	30.88	2	.03	.42	21.68	31.41	1.5	.03	.46
Food Preparation and Serving	13.64	25.79	0	.02	.53	13.76	25.88	0	.02	.53
Building and Grounds Cleaning and Maintenance	30.94	36.46	7	.07	.38	18.32	28.51	1	.02	.46
Personal Care and Service	24.13	35.47	2	.08	.44	16.72	27.7	0	.01	.52
Sales and Related Occupations	31.13	37.4	7	.08	.36	22.61	32.28	1	.03	.44
Office and Administrative Support	51.86	39.12	56	.15	.16	54.6	38.01	61	.17	.16
Farming, Fishing, and Forestry	35.74	38.47	10	.12	.21	15.39	25.15	3.5	.02	.33
Construction and Extraction	35.71	34.65	25.5	.03	.24	26.27	32.64	4	.03	.35
Installation, Maintenance, and Repair	32.97	35.02	15	.04	.28	26.39	32.14	8.5	.01	.32
Production	25.72	35	2	.05	.41	24.15	32.54	2	.03	.44
Transportation and Material Moving	20.8	32.12	1	.02	.45	21.72	31.68	1	.03	.45
Military Specific Occupations	40.81	31.69	48	.06	.1	32.17	28.42	29	.03	.19

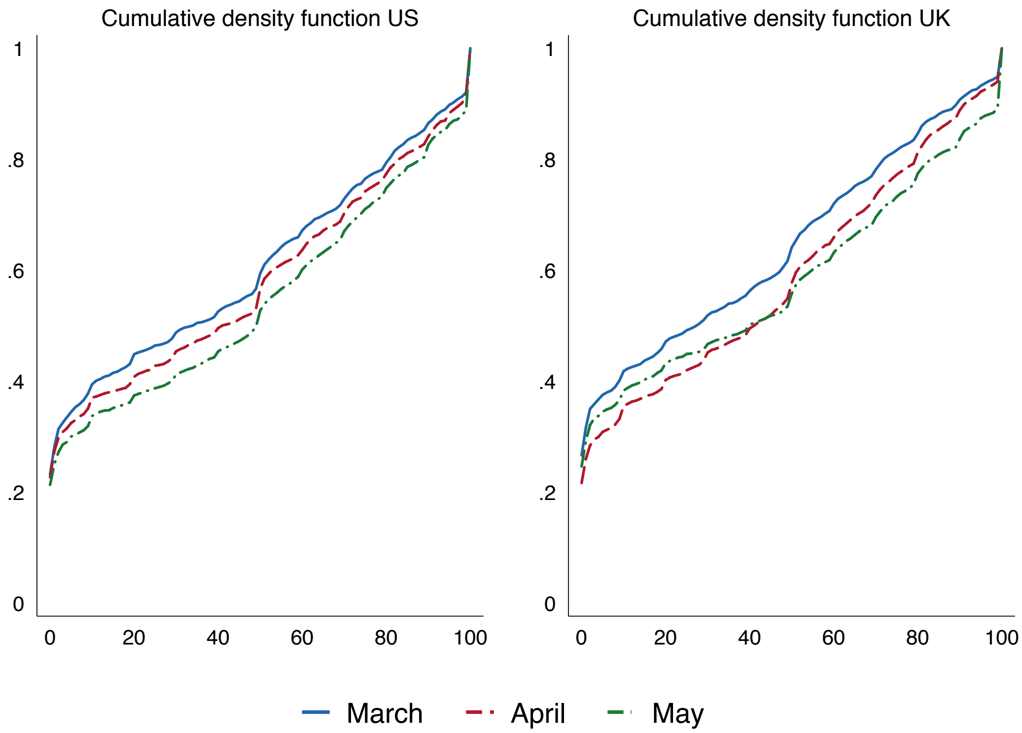
Notes: Mean, standard deviation, and median are computed using a scale from 0-100, i.e. percentages. 'Ones' are the share of respondents reporting 100%, while 'Zeros' are the share of respondents reporting 0%.

Table B.2: Summary statistics for working from home by industry

	US					UK				
Industry	Mean	SD	Median	Ones	Zeros	Mean	SD	Median	Ones	Zeros
Agriculture Forestry and Fishing	46.43	35.63	50	.06	.18	33.21	32.03	25	.05	.18
Mining and Quarrying	55.09	26.9	65	.05	.04	54.14	19.63	53	.02	0
Manufacturing	46.3	35.56	51	.08	.19	43.08	33.99	46.5	.04	.2
Electricity, Gas, Steam etc.	55.89	29.27	52.5	.11	.06	49.78	29.65	52	.08	.12
Water Supply etc.	57.1	27.23	56.5	.07	.03	54.4	24.96	58	.03	.04
Construction	43.15	33.19	47	.05	.15	46.23	34.98	50	.06	.18
Wholesale and Retail Trade	31.53	35.89	10	.05	.34	27.22	33.6	5	.03	.39
Transportation and Storage	39.19	38.33	38	.07	.28	35.91	37.41	19	.06	.3
Accommodation and Food Service Activities	15.4	26.51	0	.02	.52	19.56	29.81	1	.02	.46
Information and Communication	71.29	27.33	77	.17	.02	69.51	27.09	75	.17	.02
Finacial and Insurance Activities	66.44	32.64	77.5	.2	.06	65.67	32.08	71.5	.2	.06
Real Estate Activities	52.71	33.86	51.5	.11	.06	53.66	33.26	56	.08	.15
Professional Activities	55.83	35.52	61	.11	.12	60.27	33.48	66	.15	.07
Administrative and Support Services	50.28	37.86	53	.17	.13	53.64	35.85	56	.16	.11
Public Administration and Defence	54.9	37.07	65	.07	.16	54.52	37.88	61	.14	.19
Education	43.26	36.05	42	.09	.15	33.46	33.25	21	.05	.2
Human Health and Social Work	34.7	37.66	15	.09	.29	29.33	33.82	10	.04	.3
Arts, Entertainment and Recreation	40.66	37.82	32.5	.11	.26	39.32	38.92	26.5	.11	.27
Other Service Activities	28.71	36.79	5	.1	.38	29.83	36.96	9	.08	.3
Activities of Households as Employers	27.89	39.71	2	.11	.46	41.56	30.65	48	0	.11
Extraterritorial Organisations	57.9	23.22	63	0	.1	60	35.7	59	.33	0
Other	36.11	38.96	17	.11	.33	29.98	37.38	3	.08	.39

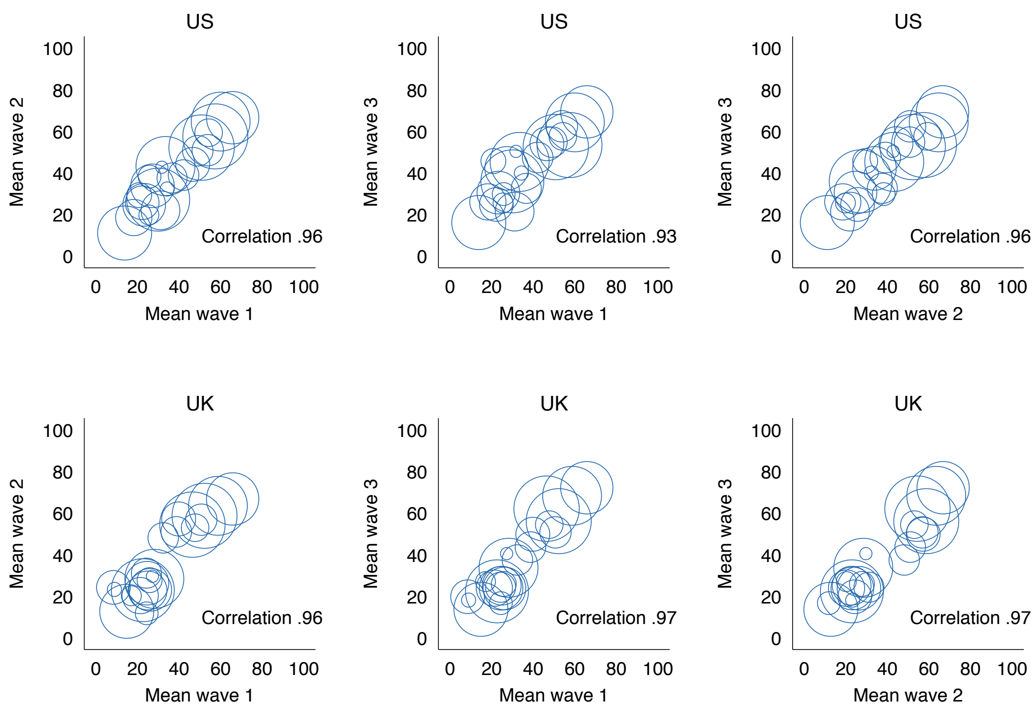
Notes: Mean, standard deviation, and median are computed using a scale from 0-100, i.e. percentages. 'Ones' are the share of respondents reporting 100%, while 'Zeros' are the share of respondents reporting 0%.

Figure B.1: Distribution of tasks that can be done from home by survey waves for the US and UK



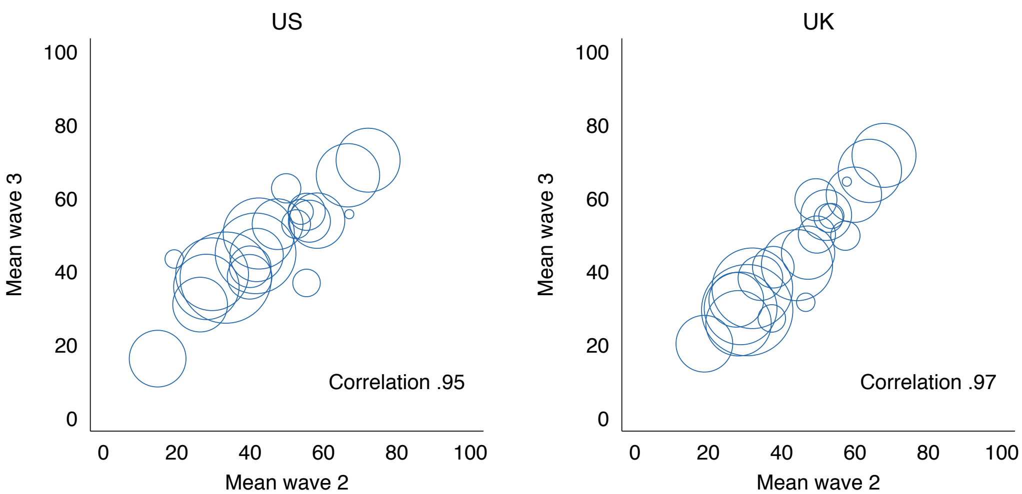
Notes: The figure shows the cumulative density functions (CDF) of the share of tasks that individuals report being able to from home in their main or last job, separately for each country and survey wave.

Figure B.2: Mean of tasks that can be done from home by occupation within countries across survey waves



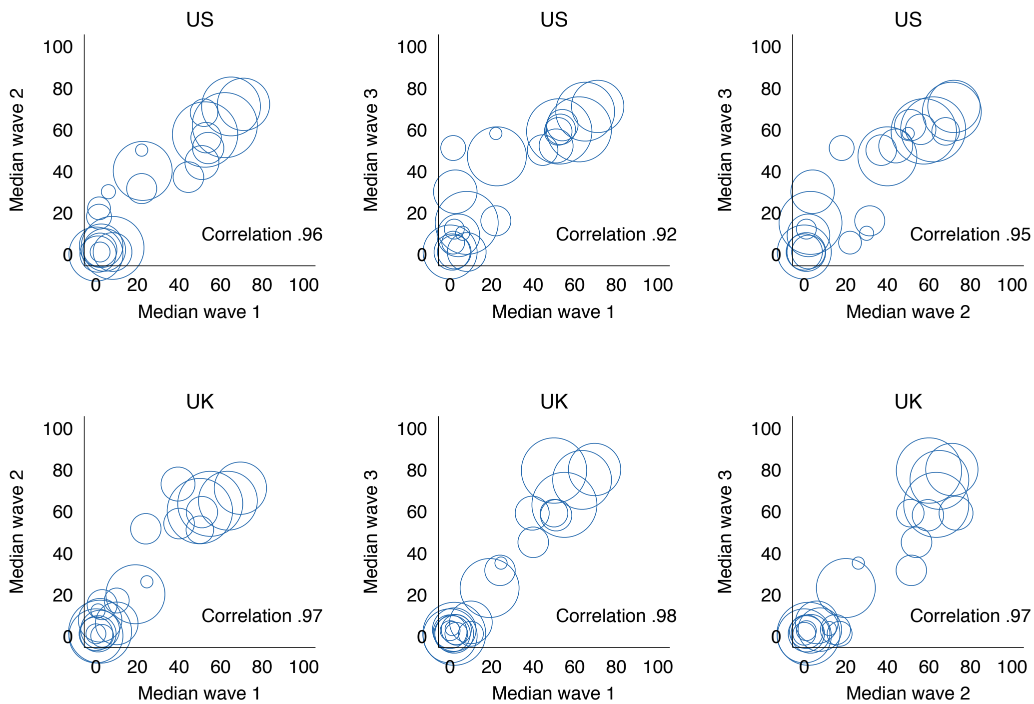
Notes: Each bubble is proportional to the number of observations and represents one occupation in the US (left) and the (UK). The x-axis and y-axis display the mean in the first, second, and third survey wave end of March, beginning of April, and mid May.

Figure B.3: Mean of tasks that can be done from home by industry within countries across survey waves



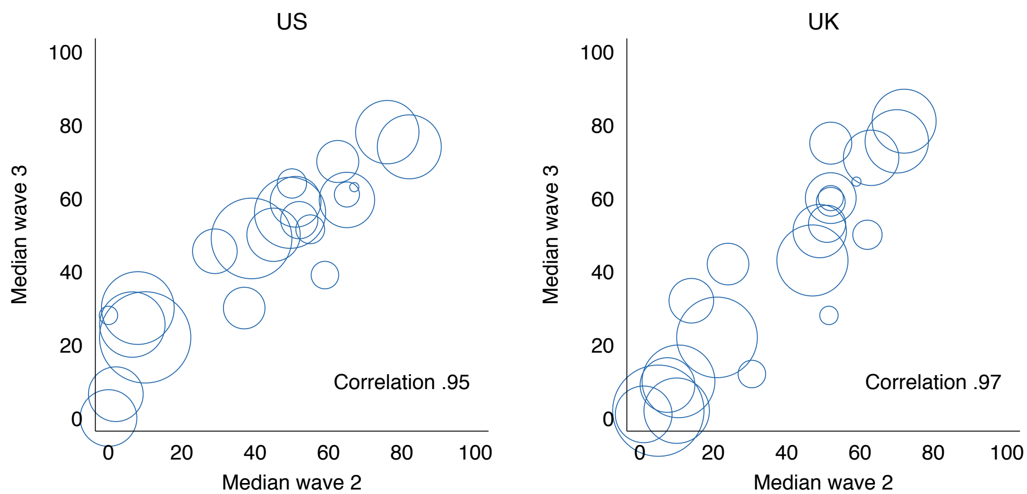
Notes: Each bubble is proportional to the number of observations and represents one industry in the US (left) and the (UK). The x-axis displays the mean in the second survey wave beginning of April and the y-axis in the third survey wave mid May.

Figure B.4: Median of tasks that can be done from home by occupation within countries across survey waves



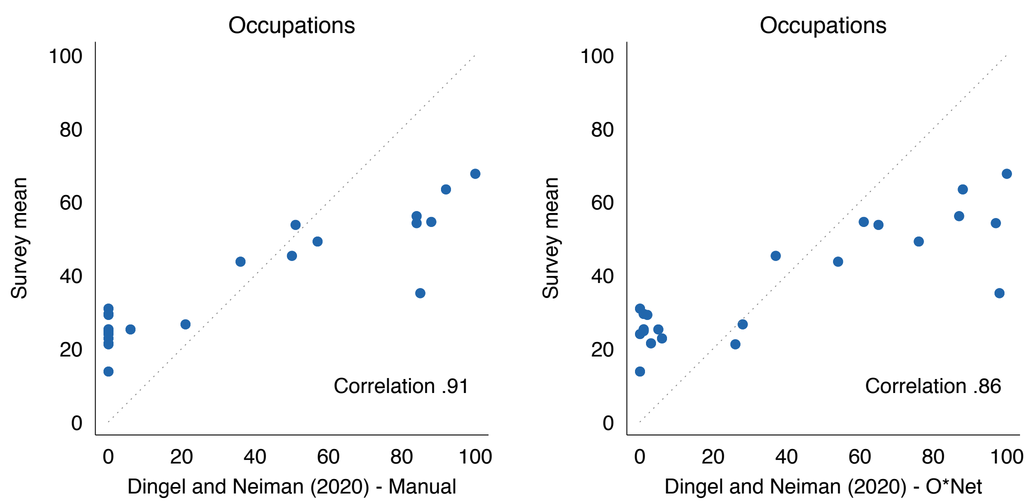
Notes: Each bubble is proportional to the number of observations and represents one occupation in the US (left) and the (UK). The x-axis and y-axis display the mean in the first, second, and third survey wave end of March, beginning of April, and mid May.

Figure B.5: Median of tasks that can be done from home by industry within countries across survey waves



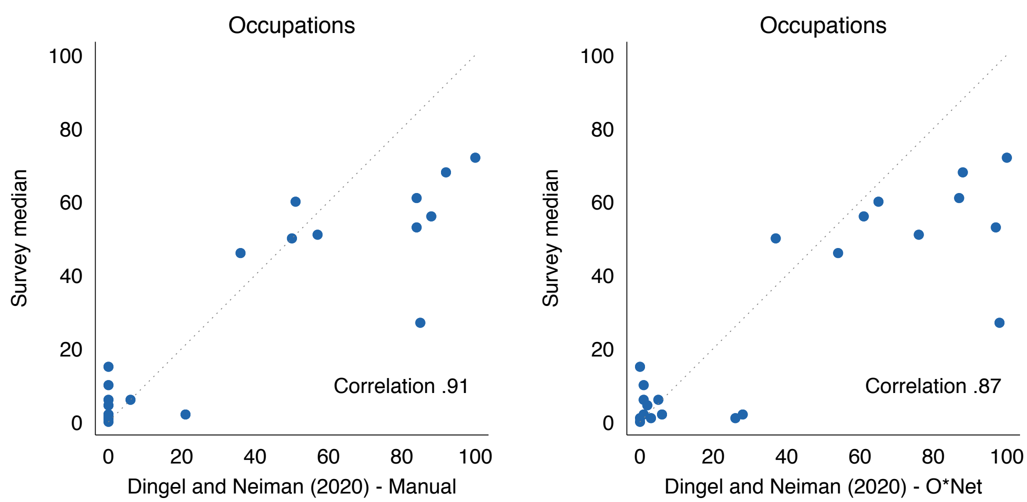
Notes: Each bubble is proportional to the number of observations and represents one industry in the US (left) and the (UK). The x-axis displays the mean in the second survey wave beginning of April and the y-axis in the third survey wave mid May.

Figure B.6: Comparison between the mean and the measures by Dingel and Neiman (2020)



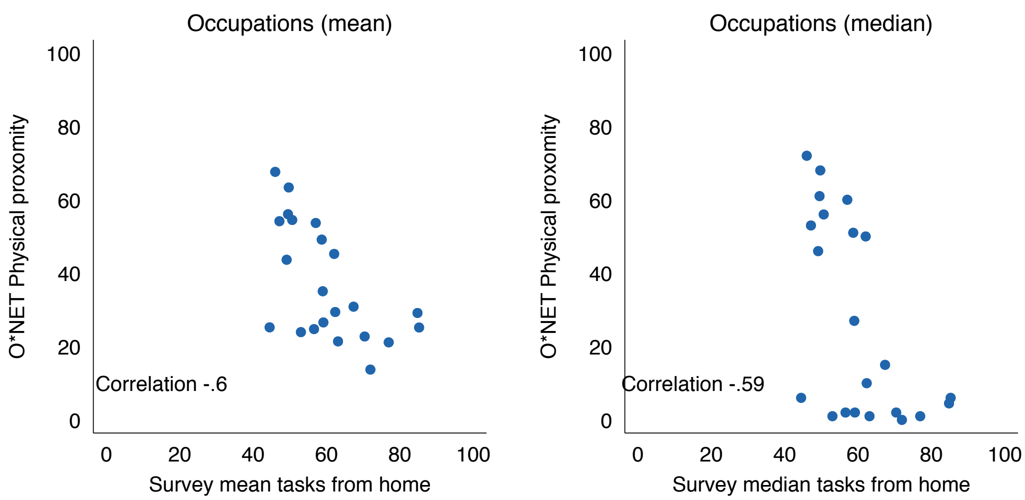
Notes: Each dot represents one occupation. The dotted line represents the 45 degree line.

Figure B.7: Comparison between the median and the measures by Dingel and Neiman (2020)



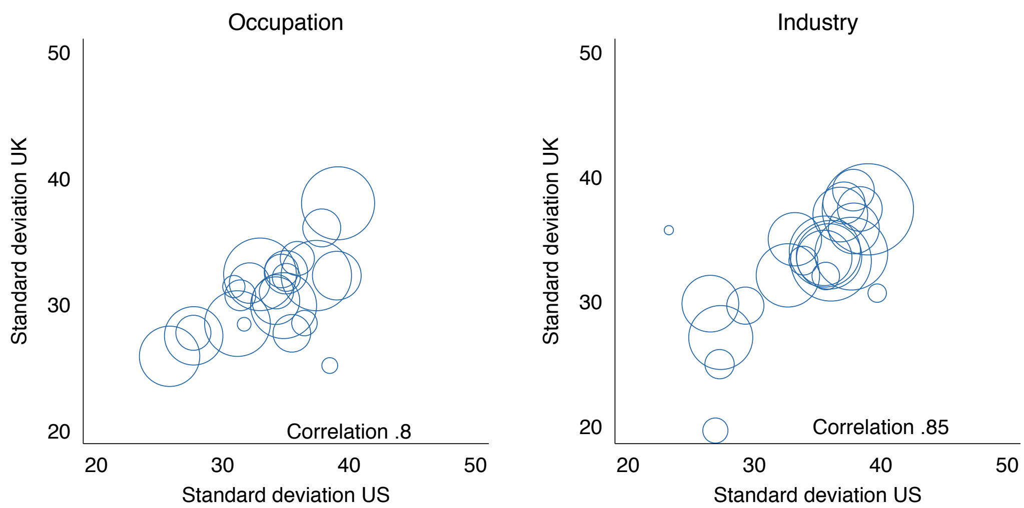
Notes: Each dot represents one occupation. The dotted line represents the 45 degree line.

Figure B.8: Share of tasks that can be done from home compared to physical proximity indicator by occupation



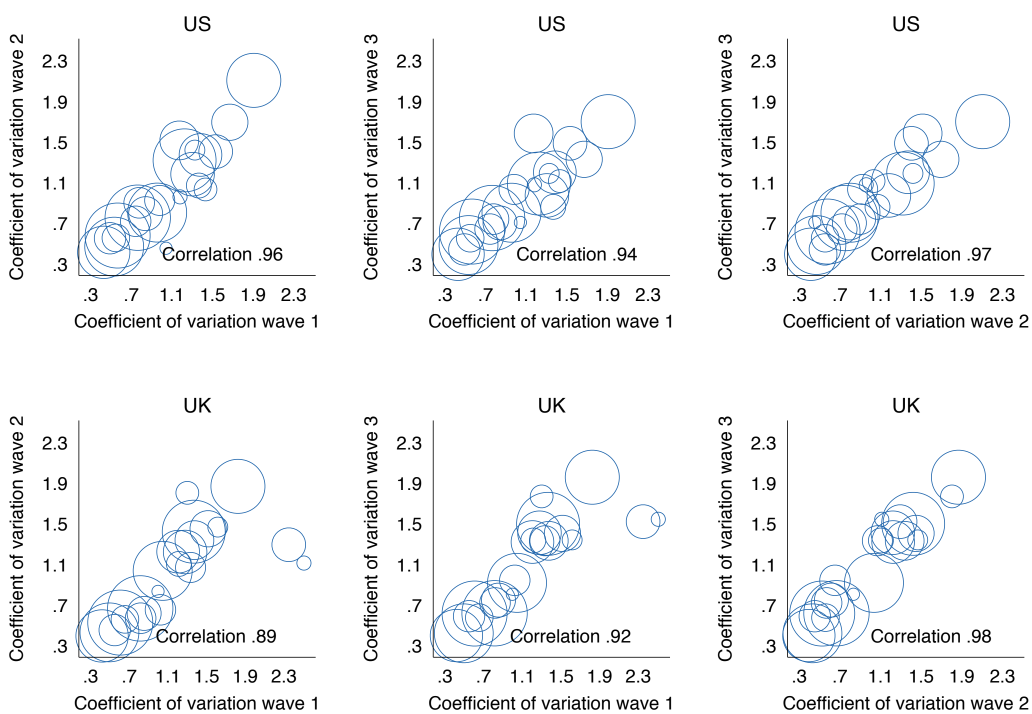
Notes: Each circle represents one occupation. The mean and median are computed using the joint US and UK sample. The physical proximity indicator is computed using the O*NET.

Figure B.9: Standard deviation of tasks that can be done from home in the US and the UK by occupation (left) and industry (right)



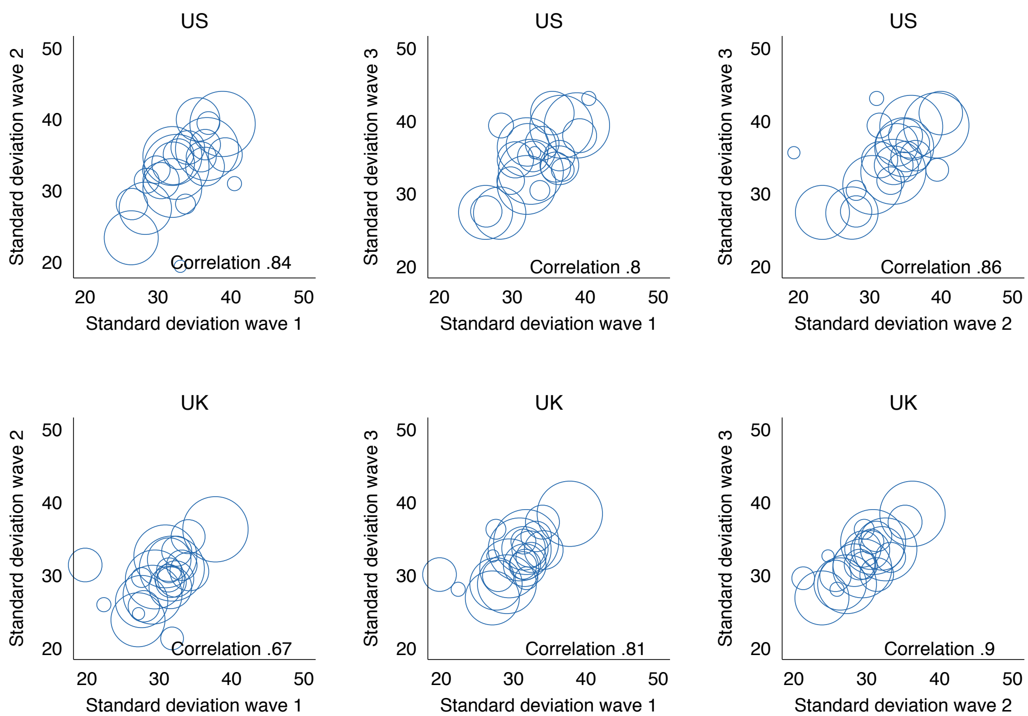
Notes: Each bubble is proportional to the number of observations and represents one occupation (left) or industry (right). The sample includes both the US and UK data.

Figure B.10: Coefficient of variation of tasks that can be done from home by occupation within countries across survey waves



Notes: Each bubble is proportional to the number of observations and represents one occupation in the US (left) and the (UK). The x-axis displays the mean in the first survey wave end of March and the y-axis in the second survey wave beginning of April.

Figure B.11: Standard deviation of tasks that can be done from home by occupation within countries across survey waves

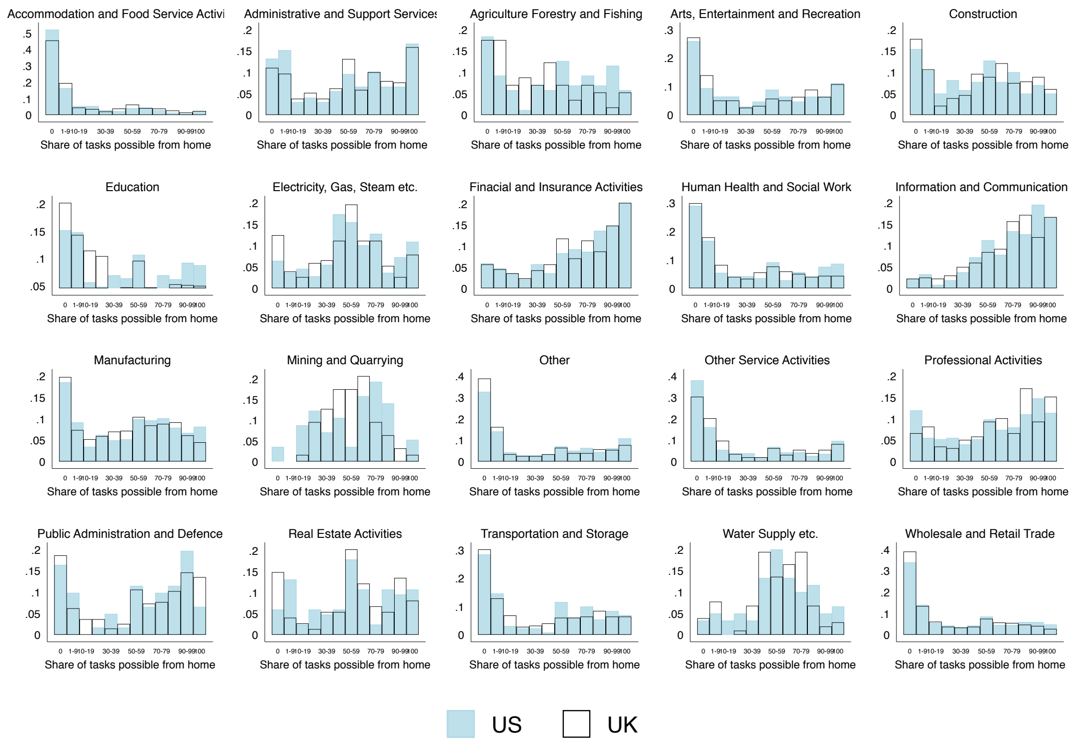


Notes: Each bubble is proportional to the number of observations and represents one occupation in the US (left) and the (UK). The x-axis displays the mean in the first survey wave end of March and the y-axis in the second survey wave beginning of April.

Figure B.12: Distribution of share tasks that can be done from home within occupations

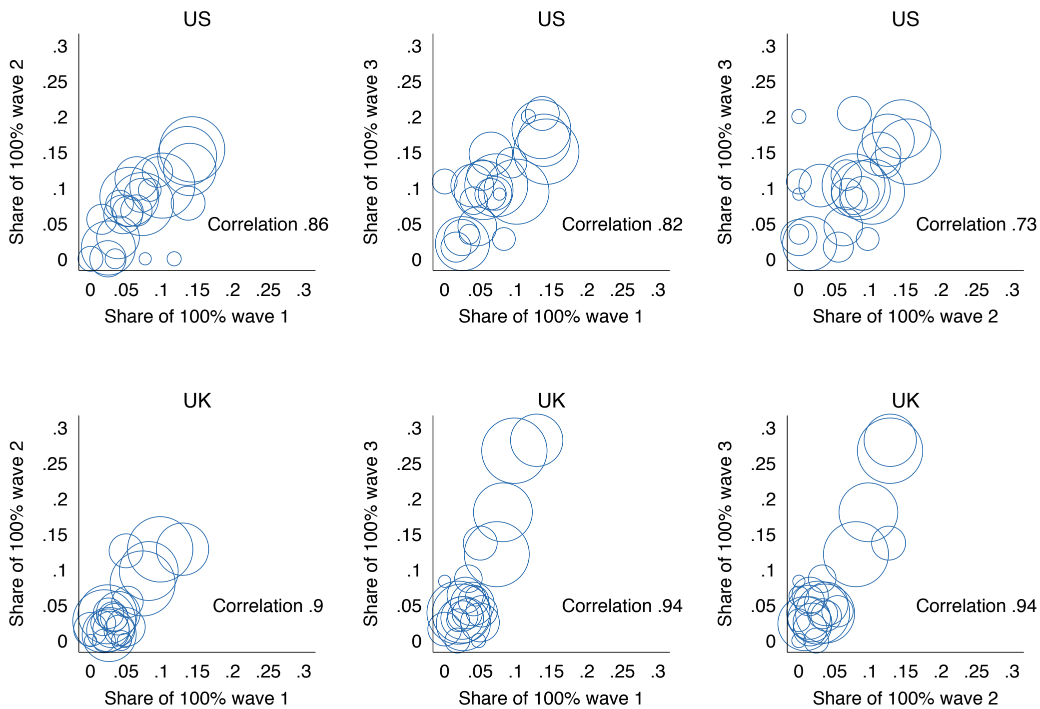
Notes: The light blue bars display the histogram for the US and the black transparent bars the histogram for the UK. We restrict the sample to occupations for which we have at least 50 observations in each country.

Figure B.13: Distribution of share tasks that can be done from home within industries



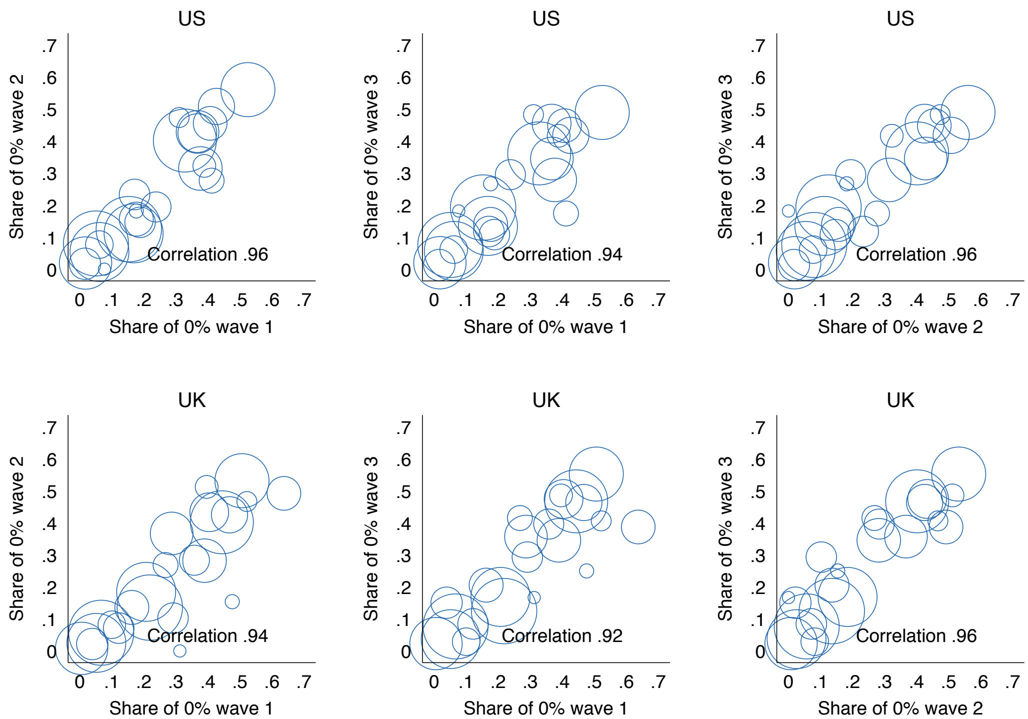
Notes: The light blue bars display the histogram for the US and the black transparent bars the histogram for the UK. We restrict the sample to occupations for which we have at least 50 observations in each country.

Figure B.14: Share of workers that can do all tasks from home by occupation within countries across survey waves



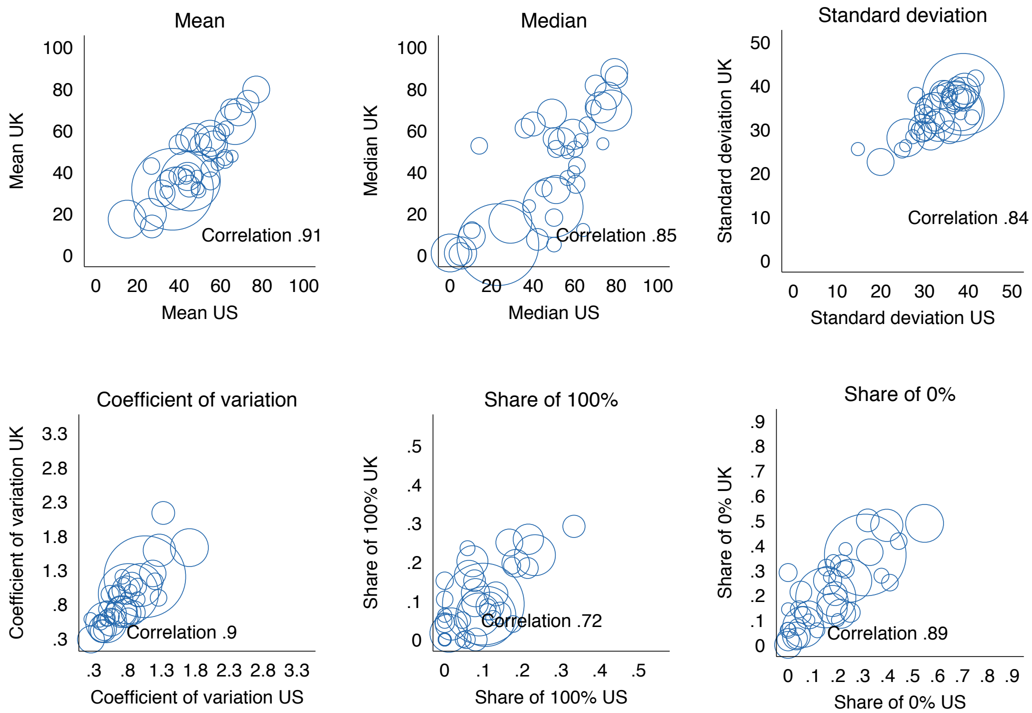
Notes: Each bubble is proportional to the number of observations and represents one occupation in the US (left) and the (UK). The x-axis displays the mean in the first survey wave end of March and the y-axis in the second survey wave beginning of April.

Figure B.15: Share of workers that can do no tasks from home by occupation the within countries across survey waves



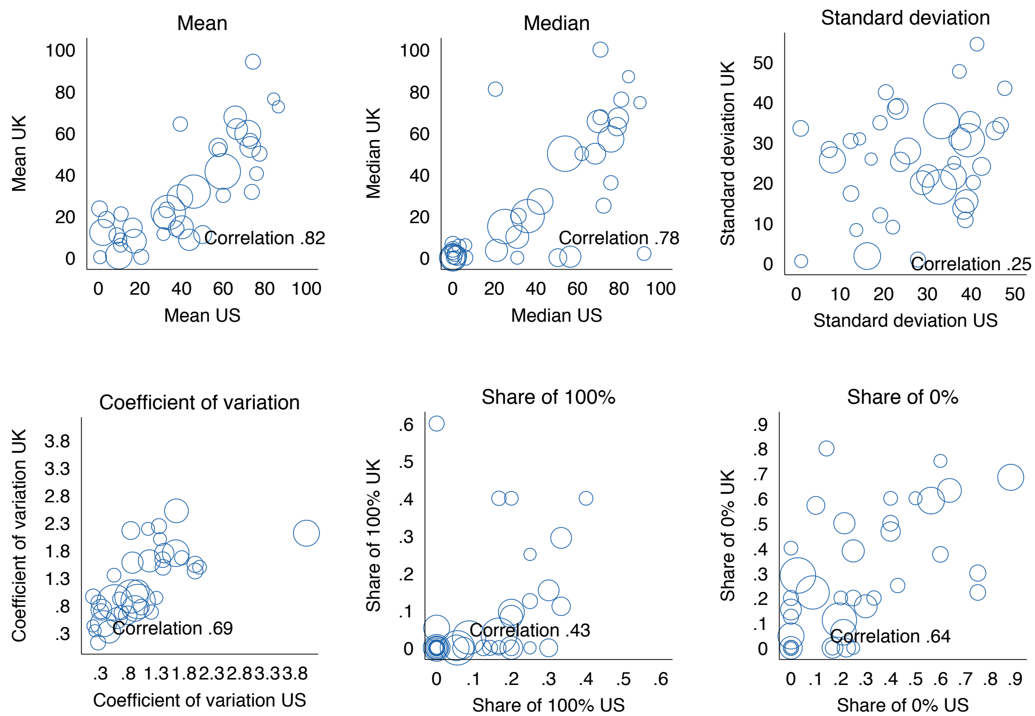
Notes: Each bubble is proportional to the number of observations and represents one occupation in the US (left) and the (UK). The x-axis displays the mean in the first survey wave end of March and the y-axis in the second survey wave beginning of April.

Figure B.16: Measures of tasks from home in the US and the UK by industry at disaggregated level



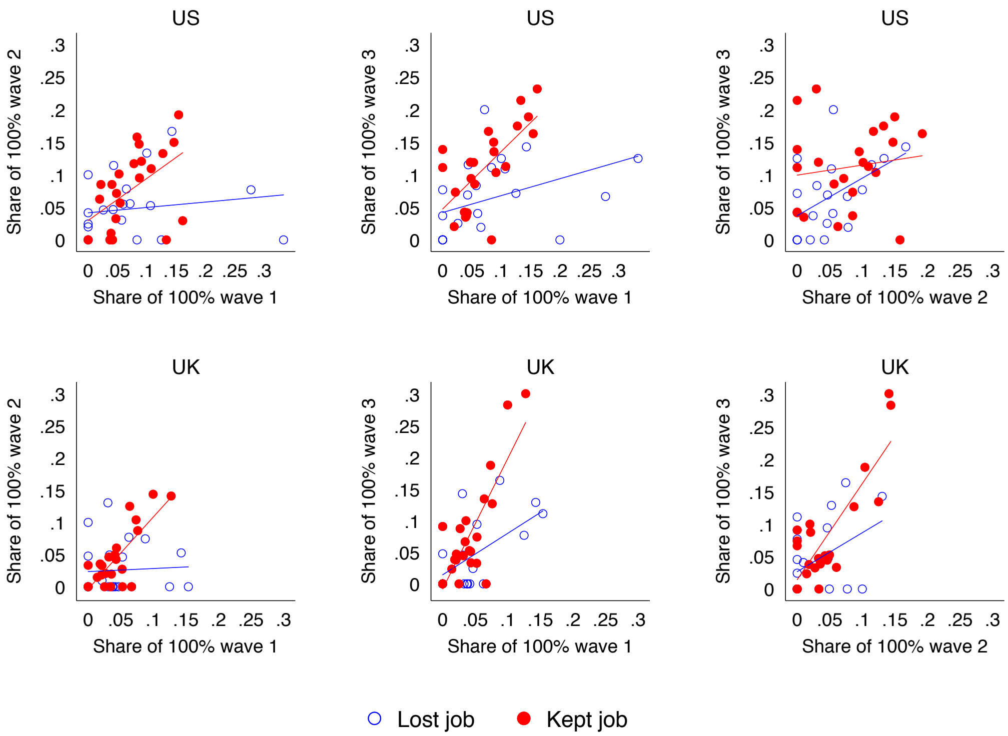
Notes: Each bubble is proportional to the number of observations and represents one industry at the disaggregated level.

Figure B.17: Measures of tasks from home in the US and the UK by occupation-industry pairs at disaggregated level



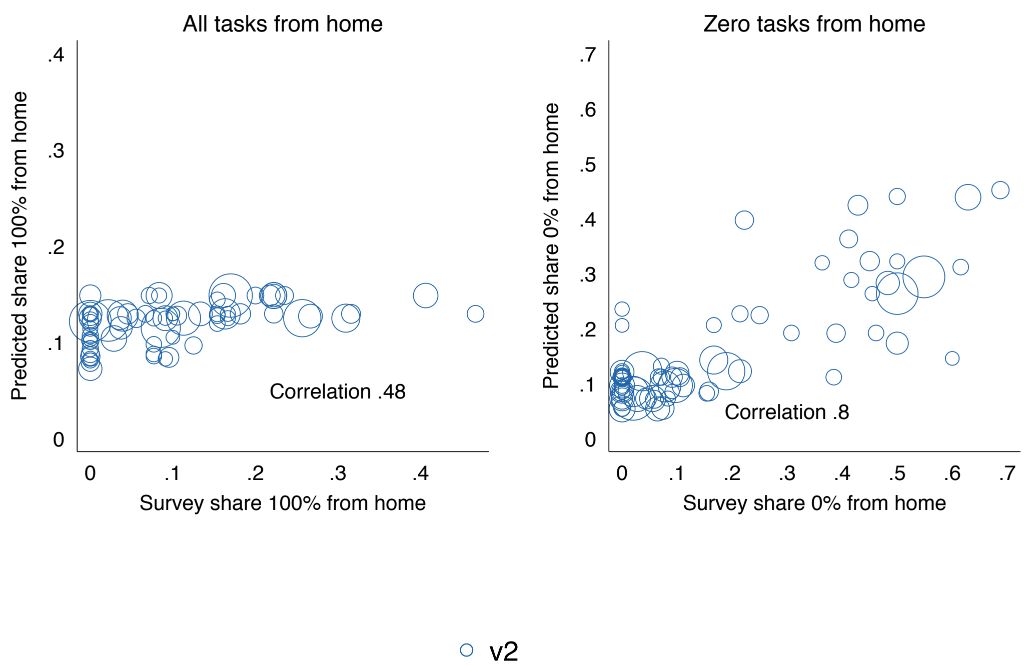
Notes: Each bubble is proportional to the number of observations and represents one occupation-industry pair at the disaggregated level. A pair has to have at least 4 observations in each country.

Figure B.18: Share of workers that can do all tasks from home by occupation within countries across survey waves depending on employment status



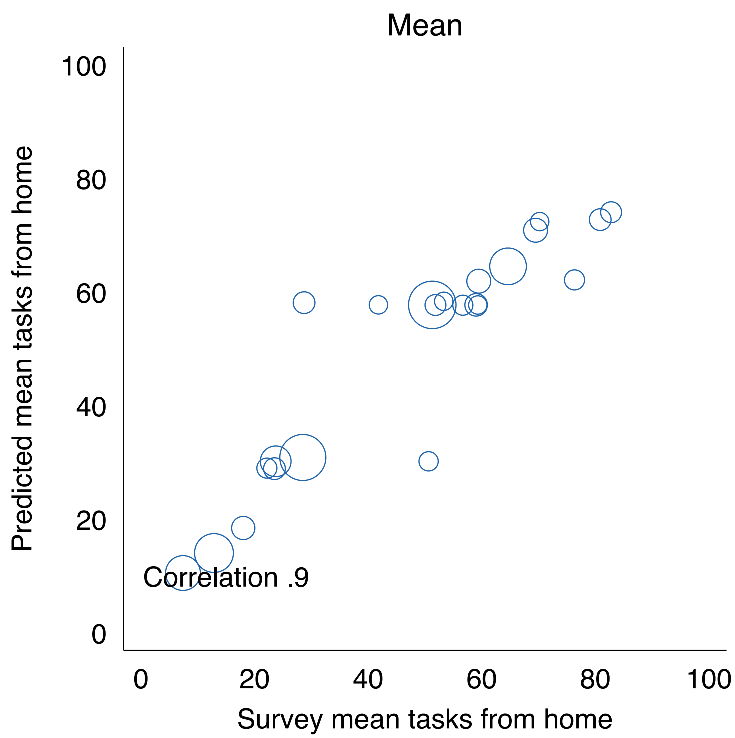
Notes: Each bubble is proportional to the number of observations and represents one occupation at the aggregated level.

Figure B.19: Share of zero and all tasks from home in survey versus predicted based on O*NET tasks



Notes: Each bubble is proportional to the number of observations and represents one occupation.

Figure B.20: Survey mean versus predicted mean for occupation based on O*NET tasks (out-of-sample)



Notes: Each bubble is proportional to the number of observations and represents one disaggregated occupation-industry pair.